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# Pedestrian's risk-based negotiation model for self-driving vehicles to get the right of way☆

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ABSTRACT

Negotiations among drivers and pedestrians are common on roads, but it is still challenging for a self-driving vehicle to negotiate for its right of way with other human road users, especially pedestrians. Currently, the self-driving vehicles are programmed for conservative behavior, yielding to approaching pedestrians. Consequently, the future urban traffic will slow down significantly. In this paper, a conceptual model of vehicle–pedestrian negotiation is proposed. This model allows individual decision making of multiple vehicles and pedestrians, extending a prior negotiation model for a single vehicle and a single pedestrian. The possible negotiation opportunities for vehicles are modeled considering different risk-taking behaviors of pedestrians. Simulation results show an overall improvement in the waiting time of vehicles and thus in the intersection throughput, compared to conservative vehicle behavior. The simulation results show also that the benefit of reduced waiting times for vehicles comes at the cost of some waiting time for pedestrians. However, the observed pedestrian waiting times in this model are not more than the generally accepted waiting times reported in empirical studies.

## 1. Introduction

In the future, human road users will share the road with self-driving vehicles (in short, 'vehicles'). Competition for space requires communication and coordination between different road participants, for example, to clarify who has the right of way and who has to wait. Except in regulated environments, this communication and coordination is currently informal between humans and will be informal with self-driving vehicles, too. Self-driving vehicles master already the recognition of pedestrians and the prediction of their movements for safe driving. Also, the industry is already experimenting with communication *channels* for communicating the self-driving vehicles' intentions to human road users (Löcken et al., 2014).

But the communication *rules*, including the vehicles interpreting and weighing the human road users' intentions, are not yet studied. This paper focuses on resolving the conflict of interests between vehicles and pedestrians to get the right of way at an unregulated intersection. This resolution is possible through an informal negotiation process, which will be specified and tested here.

Negotiation requires the exchange of cues. The vehicle will observe cues such as pedestrian's trajectories, body language, gestures, and gaze interaction. The pedestrian will observe cues such as the vehicle's driving behavior and communication channel (see above). Both parties have to agree on who may cross the area of conflict first.

The negotiation process between a single vehicle and a single pedestrian has already been studied (Gupta et al., 2018). This paper will extend the prior model. It will introduce scenarios of negotiation between multiple vehicles and multiple pedestrians. Decisions are no longer made on physical constraints alone but have now to consider some social rules as well. In addition to social rules, the vehicles will also consider different risk-taking behaviors of pedestrians.

### 1.1. Motivation

The major motivation to bring self-driving vehicles on roads is to increase the safety in traffic. As such, these automated vehicles are programmed to avoid obstacles and follow the safety-first principle (Luetge, 2017). When there is a potential trajectory conflict with any pedestrian around, the current paradigm for self-driving vehicles is yielding to them due to the lack of a two-way communication. The downside of this conservative behavior of self-driving vehicles is that it will slow down the urban traffic in future (Millard-Ball, 2018), as this paper will also show by varying the frequency of people showing up to cross the street.

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Vice versa, even with human drivers in the vehicles, pedestrians assess their risk of taking action. Risk-averse pedestrians would hesitate to cross longer than risk-taking pedestrians (Lobjois and Cavallo, 2007; Li et al., 2014; Li, 2013). Individual levels of risk-taking make pedestrian behavior harder to predict. In informal communication, the vehicle (or currently, the driver) can anticipate the pedestrian's risk and make an intuitive guess of their intended actions (Himanen and Kulmala, 1988), for example, from their gestures or gaze. Now the vehicle, if they are sure that the pedestrian's intention is to yield, can take the opportunity to pass first. Though invisible, this negotiation happens every day among drivers and pedestrians, especially at unmarked intersections.

The limitation of the previous model was that the negotiation process by a vehicle was restricted to a single pedestrian at a time. This paper overcomes this limitation by considering scenarios with multiple pedestrians having different risk-taking attitudes and then defining possible strategies for the vehicles to negotiate with them for the right of way. This paper particularly focuses on introducing a pedestrian's risk-based model for negotiation between multiple vehicles and multiple pedestrians, which is required when the vehicle is no longer driven by a human.

### 1.2. Research summary and contributions

This paper presents a novel model for negotiation, allowing vehicles to negotiate with pedestrians for the right of way. The model allows for multiple vehicles and multiple pedestrians, individual decision making, and different personalities, following some social rules. The model is designed to not compromise safety – when the vehicle is not certain[1] about agreeing with a pedestrian then it always yields to them. The *hypothesis* of this research is that a vehicle's chances for the right of way increase with negotiation, which will consequently reduce their average waiting time and improve the overall throughput at intersections when compared to the vehicle's conservative behavior.

The proposed negotiation model is implemented using the SUMO[2] traffic simulator and MATLAB[3] toolbox. In the experiments with this model, the waiting times of vehicles and the intersection throughput are analyzed for different distributions of risk-averse and risk-taking pedestrians in the pedestrian flow. These parameters are then compared to the conservative behavior model in which vehicles are slowing down when sensing pedestrians intending to cross the road.

The implemented negotiation model demonstrates how negotiations with risk-averse pedestrians improve the flow of vehicles. Compared to the conservative model, the waiting time of the vehicles is significantly improved in the negotiation model when the chances of encountering a risk-averse pedestrian are high. The results show that the overall average waiting time and intersection throughput is improved with negotiations even in the case of fewer risk-averse pedestrians in the pedestrian flow.

Thus, the contributions are:

- the first negotiation model between multiple self-driving vehicles and multiple pedestrians;
- the consideration of different risk-taking attitudes of pedestrians in order to improve vehicle throughput without compromising safety.

### 1.3. Structure of the paper

The paper is organized as follows. First, the proposed negotiation framework is discussed in Section 3. The related background study is presented in Section 2. The experiment design and simulation assumptions are discussed in detail in Section 4. This is followed by experiment results and their discussion in Section 5, and the conclusions in Section 6.

## 2. Literature review

Most road fatalities in the urban environment concern pedestrians and the main cause is human driver error (W.H. Organization, 2015). Future self-driving vehicles are expected to reduce these errors and increase the safety on roads (Winkle, 2016). However, the theoretical predictions of these vehicles' impact on traffic, in contrast, are more varied. These predictions fall into two types of impacts on the pedestrian – one emphasizing on the safe behavior of vehicles toward pedestrians, while others raising issues of their erratic behavior toward pedestrians. So far mostly theoretical reviews on the vehicle–pedestrian interactions are focused and there is far less research regarding these interactions in real-life settings.

*Safe vehicles*. The vehicles are programmed to obey the rules of the road and to wait for pedestrians to cross, even at unmarked crosswalks (Millard-Ball, 2018). When it comes to their interaction with pedestrians, the related industrial research is mainly focused on defensive measures. A passive measure of this sort is the airbag protection for pedestrians (Switkes et al., 2015) to ensure their safety. Another passive measure is a general concession to yield, expressed in research into interaction with pedestrians exploring potential communication channels for the vehicle to tell a pedestrian it sees them and is expecting them to cross in front (Keferböck and Riener, 2015). Such passive interaction measures clearly make the vehicles safer for pedestrians at the cost of the vehicle's speed. However, such safe behavior has also undesirable consequences, as discussed in one of the studies. A game theoretic analysis suggests that safer (or *conservative*) future self-driving vehicles would provoke the pedestrians to step out to cross since they trust that the vehicle will yield to them (Millard-Ball, 2018). For example, in the future it will be easy for playful children on roads to interfere with the vehicle's operations – as a consequence, the vehicle will keep standing. Theoretically, because of widespread adoption of such vehicles, the future urban traffic is expected to slow down significantly.

*Potential ambiguities in traffic*. Other researchers, however, highlight the safety concerns in mixed traffic scenarios[4] expected in future on road (Sivak and Schoettle, 2015). Replacing human drivers with autonomous systems may result in ambiguities in understanding other road users' behavior, which is evident from the recent crashes of vehicle prototypes (Richtel and Dougherty, 2015).

Social interaction among road users is necessary to guarantee everyone's safety on roads, but also to ensure proper traffic flow (Rasouli et al., 2018). There is still a social interaction void in the behavior of these vehicles. In everyday situations, human drivers tend to establish an eye contact with the pedestrians expressing their intention to pass first, while they can also judge pedestrians' intentions through their body gestures or signals such as raising a hand to stop or waving to let others pass (Langton et al., 2000). In such situations, either the driver or pedestrian, yield to the other to maintain safety on roads. Such negotiations for the right of way are common on roads. However, for a self-driving vehicle, mimicking such a behavior has few challenges, one of them being the non-universality of signaling gestures (Gupta et al.,

[1] In the real world, vehicles have to use machine learning methods to learn pedestrian's intentions based on their gestures and other behavior. This sensing and data analytics process by the vehicle is out of the scope of this paper. Instead, we start with a certainty estimate. A certain agreement or disagreement in this paper means that the vehicle is 'nearly' able to predict the pedestrian's intentions, for example, it can clearly distinguish between a moving and a stopped pedestrian – this assumption is based on existing literature and promising advancement in the machine learning technologies with applications to automated driving.

[2] http://sumo.dlr.de.

[3] http://mathworks.com.

[4] Self-driving vehicles sharing the road with human road users.

2016). Also, these social cues may be ignored by some pedestrians and drivers (civil inattention) leading to indiscipline on roads (Özkan et al., 2006; Kadali and Vedagiri, 2013; Patterson et al., 2007; Goffman, 1963). These situations exacerbate the challenges for future vehicles.

Some research argues already that the future self-driving vehicles are required to exhibit a socially acceptable behavior that is understood by human road users, especially pedestrians (Müller et al., 2016; Shladover, 2016). One such aspect of this social behavior is traffic negotiation with pedestrians, which is addressed in this paper. This paper attempts to consolidate the observed elements of social behavior in traffic into a negotiation model for vehicles and pedestrians. From the above review, assuming that as long as these social rules are lacking, the design of these vehicles' behavior will be conservative; this paper aims to improve traffic throughput by active social engagement.

*Pedestrian's risk-taking attitudes*. The proposed model considers also different personalities of pedestrians with regard to their risk-taking attitudes. Any traffic situation largely depends on the behavior of pedestrians (and drivers) toward others in traffic. The risk of being hit keeps pedestrians typically on the sidewalk, but this behavior varies among places and cultures. For example, pedestrians in Manhattan uphold their right of way at unmarked crosswalks and do not hesitate to cross first; however, in other parts of the United States, pedestrians are found to be more risk-averse due to frequent road rules violations by drivers (Schneider and Sanders, 2015). In crowded spaces, on contrary, the drivers adjust to the unpredictability of pedestrians and modify their speed and behavior accordingly. When it comes to self-driving vehicles, the trust of pedestrians toward the predictability of their behavior is less. Recent human subject studies have shown pedestrians' unwillingness to cross in front of self-driving vehicle prototypes (Lagstrom and Lundgren, 2015). However, other similar studies report a mix of risk-taking and risk-averse behavior of pedestrians encountering the self-driving vehicle prototypes (Palmeiro et al., 1020).

Also, the perception of a safe gap in traffic is individually different. Young pedestrians show a higher tendency to risk-taking, in contrast to older people who show a more cautionary behavior while crossing (Oxley et al., 1997). Children often lack the perception of the safe gap altogether (Schmidt and Färber, 2009; Demetre et al., 1992). Analytical approaches to risk analysis of pedestrian's crossing behavior have revealed their interesting waiting time distributions. According to Li (2013), the waiting time of a population that consists of both risk-taking and risk-averse pedestrians, in general exhibits a U-shaped distribution. This explains that risk-taking pedestrians become impatient as their waiting time increases. In contrast, the longer waiting risk-averse pedestrians are less likely to cross the street (Li et al., 2014). However, their hesitation to cross is reduced if their neighbor has started crossing, further suggesting that groups may pursue more unsafe crossing behavior (Faria et al., 1242). The negotiation concepts presented in this paper will be considering different risk-taking behaviors of the pedestrians deduced from the above empirical studies.

## 3. Risk-based vehicle–pedestrian negotiation model

Negotiation is commonly defined in the business literature as the *'process of combining conflicting positions into a common position, under a decision rule of unanimity'* (Zartman, 1988). In this work, the negotiation is conceptualized as a process in which both parties – vehicles, and pedestrians – take steps to agree on an outcome, i.e., on who has the right of way to pass the conflict point first. Also, every party seeks to make that outcome favorable to them, i.e., minimize the waiting time considering the risk involved.

The interaction environment is any unmarked location along the road network where at least one passenger shows intend to cross. This intention can happen at unmarked intersections, or the pedestrian can consider jaywalking. In the implementation of the proposed model, an unmarked intersection is assumed, where pedestrians approach the road of the vehicle from the intersecting road (Fig. 1). Pedestrian and vehicle trajectories can be extrapolated from their current location, speed, and heading. These extrapolated trajectories will be on collision or near collision with the vehicle considering its options. For these selected pedestrians a negotiation must entail. In this work, this factor is called as *risk* (of collision). It can be implemented for example by a simple linear model which is discussed in Section 3.1.

Negotiation also depends on the risk-taking attitude of pedestrians toward vehicles. Pedestrians may or may not accept the street-crossing risk when the vehicle is approaching from a conflicting direction. The perception of a safe gap from the vehicle is individually different (Cohen et al., 1955); few people tend to take higher risks than others. Pedestrian behavior, in literature, is studied as two types: a *risk-taking* pedestrian who is willing to cross first when confronted with a vehicle, and is less likely to yield; another type is a *risk-averse* pedestrian who is likely to yield to the vehicle as they are not willing to accept the risk. This model considers these two types of pedestrian behaviors during negotiation. However, this pedestrian behavior is dynamic and is often influenced by other social factors.[5] This change in behavior is also considered in the proposed model which is further discussed in Section 3.2. After discussing the implementation details of pedestrians' risk and behaviors in this model, this section then describes the possible negotiation cases based on the risk to a pedestrian (Section 3.3). This is followed by a description of the overall proposed conceptual model of negotiation (Section 3.4).

### 3.1. Pedestrian risk computation

The situation studied here is depicted in Fig. 1. The *conflict point*, represented by red dots in Fig. 1, is where the pedestrian's trajectory intersects with the vehicle's trajectory. At any instance, $t_v$ denotes the current predicted time required by the vehicle to reach the conflict point, and $t_{pi}$ denotes the current predicted time required by the *i*th pedestrian to reach the same point. These times can be estimated with their current locations, speeds, and headings.

Different pedestrians intending to cross the road are at different degrees of risk of collision with the vehicle. This risk depends on the overlap in their predicted time to reach the conflict point ($t_{pi}$) with that of the approaching vehicle ($t_v$). Moreover, it also depends on the total time taken by the pedestrians to walk from the starting edge of the intersection until the end of the lane crossing (denoted by crossing time $c$).

In this model, the risk to each pedestrian is mapped in the range [0,1]. As represented in Fig. 1, the risk to a pedestrian is maximum (= 1) if their time to reach the conflict point is the same as that of the approaching vehicle ($t_p = t_v$), i.e., a collision is imminent if none of the parties changes their behavior. This risk linearly increases if the pedestrian is expected to reach a location between the starting edge of the intersection and the conflict point, when the vehicle is expected to pass the conflict point ($t_p > t_v$). Similarly, the pedestrian's risk decreases if the pedestrian is expected to pass the conflict point but is still before the end of the lane edge ($t_p < t_v$). The risk is zero if the difference in their arrival times is greater than the crossing time $c$ of pedestrians. Thus, the pedestrians are at no risk when either they are expected to finish crossing before the vehicle reaches the conflict point, or if the vehicle will pass before they arrive near the curbside. Hence the risk to a pedestrian is formulated as in Eq. (1)

$$\text{risk} = \begin{cases} 1 - \frac{t_v - t_p}{c/2}, & t_p < t_v \\ 1 - \frac{t_p - t_v}{c/2}, & t_p \geqslant t_v \\ 0, & |t_v - t_p| \geqslant c/2 \end{cases} \tag{1}$$

Note that the vehicle and pedestrian are considered as point objects

[5] Studies in behavioral psychology have identified the factors influencing the social behavior of pedestrians (Ishaque and Noland, 2008; Harrell, 1991).

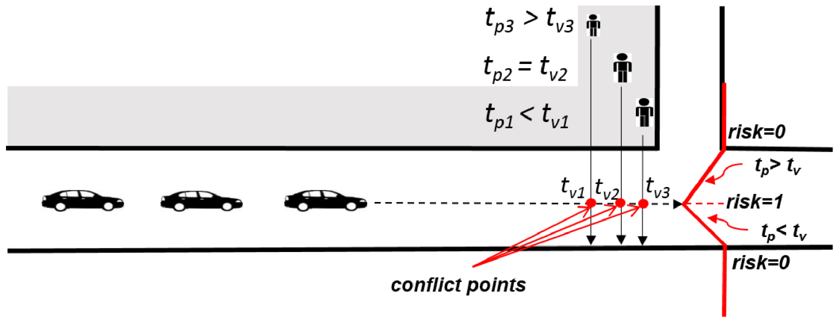



**Fig. 1.** Interaction scenario, also showing pedestrian's risk computation.

for risk computations, and the width of the vehicle is not taken into account. In the latter case, the risk mapping can be done by considering a conflict zone instead of a conflict point which does not change the concepts presented here. Also, this paper assumes that pedestrians are walking at a constant speed. Negotiation is a continuous process until an agreement is reached which is explained in detail in Section 3.4 This means that the risk to a pedestrian is re-assessed at every timestep which captures any changes in the pedestrian's behavior at the next instance, including any change in their walking speed or in their action to stop at the curb for safety reasons. So assuming a constant walking speed for pedestrians until they stop doesn’t affect the model.

**Table 1**
Possible cases of risk to the pedestrians and corresponding action by the vehicle in that situation.

| Pedestrian's risk | Action by the vehicle |
|---|---|
| *risk* = 0 | No negotiation required, vehicle keeps accelerating until it attains the maximum speed |
| 0 < *risk* < 0.5 | Vehicle keeps moving with the current speed and monitors the pedestrian's action |
| *risk* ⩾ 0.5 | Vehicle starts negotiating as follows:<br>(a) if (alert by vehicle) then *vehicle moves*<br>(b) if (pedestrian is *RA*) then *vehicle moves*<br>(c) if (pedestrian is *RT*) then *vehicle slows down* |

### 3.2. Pedestrian behavior

In reality, people (even risk-averse), have limited patience. Literature has shown that with growing waiting time they become impatient (Li, 2013; Li et al., 2014). Empirical studies on pedestrians’ waiting times have found that their impatience and risk-taking behavior increase after 20 s of delay (Kaiser, 1994). Similarly, even risk-taking pedestrians do not want to compromise their safety and consider physical constraints before taking a decision to cross (Li et al., 2014). Pedestrians may also be affected by the behavior of others at crossings; they are more likely to cross if pedestrians next to them have started crossing (Faria et al., 1242).

In this paper, every pedestrian is categorized based on their risk-taking behavior as either *risk-taker (RT)* or a *risk-averse (RA)*. A risk-taking pedestrian is not willing to yield to the approaching vehicle unless the vehicle has notified an alert that it cannot stop in time (called as *alert* status of the vehicle). In the latter case, every pedestrian waits for the vehicle to pass. A risk-averse pedestrian, in general, waits and yields to the vehicle when the risk to them is high. However, risk-averse pedestrians do not wait longer than their maximum waiting time limit (around 20 s) and trigger a stepping out action after this time. This model also assumes that if there is any risk-taker next to them who sets off first, then a risk-averse pedestrian will start following them. In such situations, if physical constraints do not allow the vehicle to stop before time, then it notifies the pedestrians through an alert. Else, the vehicle slows down.

### 3.3. Possible negotiation opportunities for vehicle

The possible actions by the vehicle for different degrees of perceived risk to the pedestrians are shown in Table 1. If the risk to the pedestrian is zero, then there is no negotiation required and both parties can move with their current or maximum speed. As the approaching vehicle and pedestrians come closer to the conflict point with time, the risk to the pedestrians starts increasing (*risk* > 0). Initially, when the risk is low (< 0.5), the vehicle keeps moving at the current speed while monitoring the movement of pedestrians. However, when the overlap in the time of arrivals of both parties increases, the risks to pedestrians also increases (*risk* > 0.5).

The traffic situation at any time will be a mix of pedestrians who are at different degrees of risk – some may be at high risk and few may be at no risk. The vehicle, however, can only broadcast a common signal to the approaching pedestrians, so it waits until there are only high-risk pedestrians near the curb side to negotiate with. In the implementation of this process, if some pedestrians moving ahead in the crowd are at no risk, then the vehicle waits to broadcast its negotiation request till they finish crossing. Once the zero-risk pedestrians have finished crossing, the vehicle broadcasts its negotiation request to those at risk. At this stage, if the vehicle cannot stop then it broadcasts the message to pass first and notifies an *alert* status to the pedestrians. Else, negotiation by vehicle depends on the behavior of the pedestrians at risk. The vehicle has an opportunity to pass first if the pedestrian is risk-averse (*RA*) who hesitates to take the high risk. However, if any pedestrian (at risk) is a risk-taker then they are tempted to cross first despite being in a risky situation. In the latter case, the negotiation request by vehicle is ignored or rejected by a risk-taker and the vehicle yields to the pedestrians. In the next section, the overall stepwise negotiation process is discussed which is followed by a simulation example to explain the proposed model.

### 3.4. Conceptual negotiation model

The conceptual model for negotiation is presented in Fig. 2. This model shows the negotiation of a vehicle with the *i*th pedestrian at a time instance *t*. It is assumed that the vehicle's intentions are broadcasted as a common signal to all the competing pedestrians in the scene. The vehicle estimates the model parameters for every pedestrian in the scenario who is competing for the right of way. The model is described as follows:

1. *Detection and communication*: With advanced machine learning technologies, any changes in the environment, including a pedestrian's movement, gestures, and gaze, can be detected by the vehicle's sensors (Rasouli et al., 2017). In this model, the speed and direction of movement are the primary behavioral properties of a negotiating party to indicate their intentions. The other cues such as gestures and eye gaze (of the pedestrian) are secondary. It is assumed that both parties can communicate their intentions via a

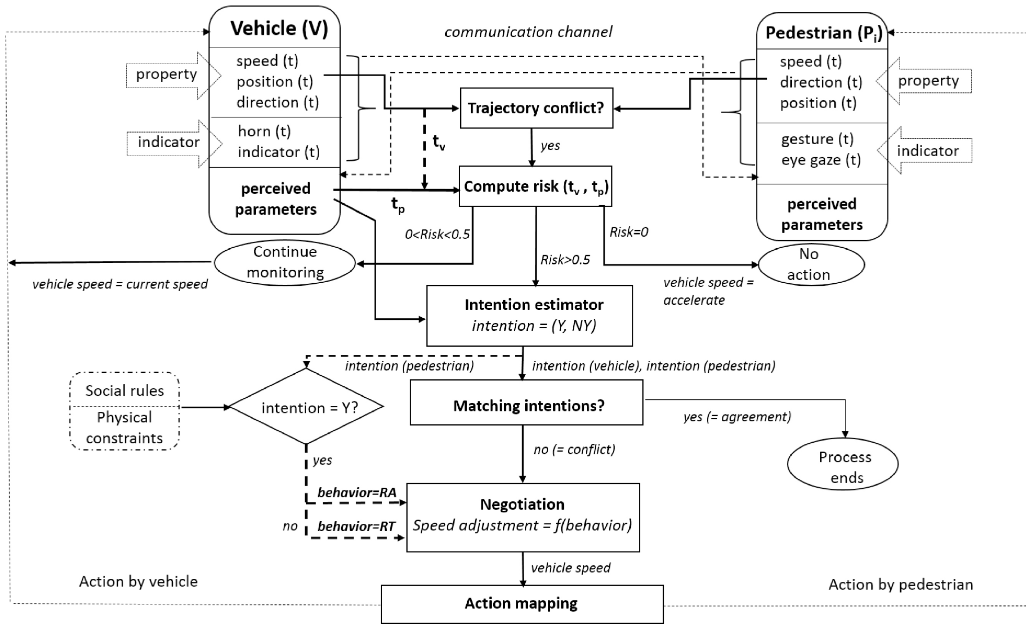



**Fig. 2.** The proposed vehicle–pedestrian negotiation framework.

communication channel, either to acknowledge the signals from another party or to indicate their own intentions.

2. *Check for trajectory conflict*: The vehicle first checks for any trajectory conflict with the pedestrian. If there is no conflict then there is no need for any negotiation, else the following steps apply.
3. *Estimate risk to pedestrian*: In case of a potential trajectory conflict, next the vehicle estimates the risk to the pedestrian using Eq. (1) as described in Section 3.1. If the risk is zero or less than 0.5 (low risk), then the vehicle acts as described in Table 1. However, if the pedestrian is at a higher risk then the vehicle has to know the intention of the pedestrian.
4. *Predict intention and behavior of the pedestrian*: The vehicle estimates the pedestrian's intention based on the perceived pedestrian parameters.[6] The intention of a pedestrian, in this model, is represented in terms of chances of them yielding ($Y$) and not yielding ($NY = 1 - Y$) to the vehicle. This intention value gives an idea to the vehicle whether the pedestrian is risk-averse (RA when $Y \gg NY$) or a risk-taker (RT when $NY \gg Y$). In case the vehicle is unsure about this behavior, it falls back to the safety principle and eventually slows down.
5. *Is there an agreement?* The vehicle is continuously looking for an agreement with the pedestrian. An agreement in the negotiation is reached when the intentions of the two parties match. For a vehicle-favored negotiation, matching intentions means that the pedestrian has indicated to stop for the vehicle when the vehicle intended to pass first. Conversely, a negotiation in favor of the pedestrian intending to cross first requires that the vehicle indicates to slow down (intentions of both parties matched). However, if both parties have conflicting intentions to get the right of way first then the vehicle has to start negotiating.
6. *Negotiation*: At this stage, the vehicle has an opportunity to negotiate as the pedestrian is at risk. This, however, depends on the behavior of the pedestrian. The behavior depends on the pedestrian types and is influenced by social rules and physical constraints; all this is already discussed in Section 3.2. Based on the vehicle's perceived behavior of pedestrian (in *Step 4*), it decides to move or slow down as discussed in Table 1.
7. *Action mapping*: After this step, both parties indicate their intentions in the form of some signal as described in *Step 1* and the negotiation cycle continues until an agreement is reached. At the next instance, there may be a change in the intentions of any party. For example, a pedestrian may slow down and gesture to stop (acknowledging the vehicle's right of way request), in which case an agreement is reached, and the vehicle passes first. If there is no acknowledgment from either side, the negotiation cycle continues to seek an agreement till it is safe to do, else the vehicle prepares to slow down.

### 3.5. *Example scenario*

Two negotiation example scenarios are presented in Figs. 3 and 4. The negotiation process is discussed below for each of them. In these examples, six pedestrians are approaching the intersection ordered by their time of arrivals at the intersection: $P1$, $P2$, …, $P6$. The vehicle is approaching the intersection from another direction. These examples show the risk to each pedestrian at different timestamps as the vehicle approaches the conflict point, along with the estimated time taken by them to reach that point ($t_p$ and $t_v$).

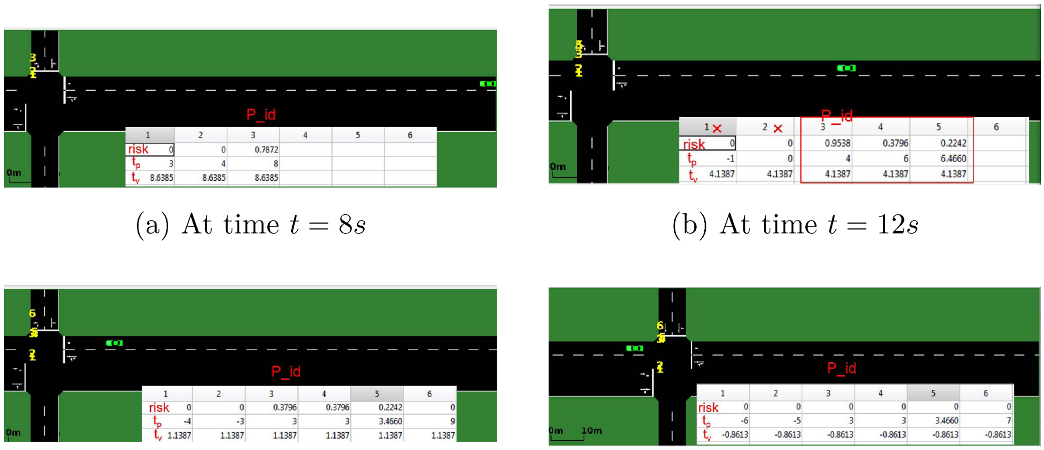
*Case 1: Encountering risk-averse pedestrians*. Suppose these pedestrians are risk-averse. Initially, no negotiation is happening as risk is zero for pedestrians in front of the queue ($P1$ and $P2$) and they have not yet finished crossing (Fig. 3a). Meanwhile, the vehicle keeps accelerating if its speed is not maximum. For pedestrian $P3$, the risk is high, but all parties keep moving as the vehicle is not negotiating yet.

When $P1$ and $P2$ have finished crossing (Fig. 3b), the vehicle starts negotiation as $P3$ is at a high risk ($risk > 0.5$). The negotiation message is broadcasted by the vehicle to the pedestrians (who have not yet started crossing).

These pedestrians (including $P3$) are risk-averse, so $P3$ signals to yield to the vehicle and stops, and the other pedestrians being risk averse also stop (Fig. 3c). The vehicle broadcasts the message that it is speeding up to pass first (agreement), and the vehicle passes through the intersection in the next few seconds (Fig. 3d).

*Case 2: Encountering risk-taking pedestrians*. In the same example after Step 2 in Fig. 3c, if $P3$ is a risk-taker then the situation is different. $P3$ takes a risk and keeps moving toward the intersection with the intention to cross first. This movement signal from the pedestrian forces the vehicle to slow down or even to stop (Fig. 4a).

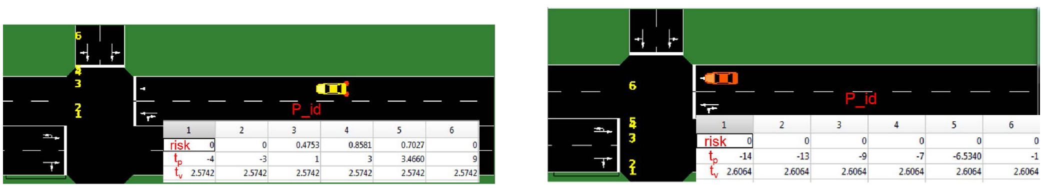
[6] In the context of intention estimation, algorithms have already developed in the existing literature to detect the possible actions of pedestrians and drivers (Rasouli et al., 2017; Molchanov et al., 2015).



(a) At time $t = 8s$ (b) At time $t = 12s$

(c) At time $t = 15s$ (d) At time $t = 17s$

**Fig. 3.** Time series simulation (in SUMO) example to show the proposed vehicle–pedestrian negotiation with risk-averse pedestrians.



(a) At time $t = 15s$ (b) At time $t = 25s$

**Fig. 4.** The previous example in Fig. 3 with risk-takers.

The slowing down of the vehicle reduces the risk to other approaching pedestrians *P*4 and *P*5 who were also at high risk before (they were walking closely behind *P*3). Whether these pedestrians are risk-takers or risk-averse, the slowing down signal from the vehicle encourages them (*P*4 and *P*5) to cross with *P*3. Now *P*6 is far behind *P*5 due to the temporal gap, so the vehicle still has an opportunity to negotiate with *P*6. In this example, since *P*6 is also a risk-taker who is not willing to wait so the vehicle continues to wait until *P*6 finishes crossing.

In the above examples for the same interaction scenarios but different types of pedestrian behavior, the exit timestamps of the vehicle differ by about 8 s. This is a simple example. The experiment design to test the research hypothesis, in the next section, aims to assess the overall traffic flow when a number of vehicles are interacting with a mix of *RA* and *RT* pedestrians.

## 4. Experiment design

The proposed negotiation model is simulated using SUMO (Simulation of Urban Mobility) and MATLAB. The two interact using the TRACI protocol in a client-server scenario. The model is implemented in MATLAB using motion parameters from the SUMO server, and the visualization is done in SUMO. The simulation runtime is around seven hours (24,000 steps of 1 s each) for each of the experiment cases. Few assumptions in the design are:

1. The environment considered is an unregulated road intersection and the vehicles are moving along a straight line on the road; there is no lane changing or passing around the pedestrian.
2. Vehicles enter and exit the simulation in the same order; there is no overtaking.
3. The current model considers only the vehicle's interaction with the pedestrians approaching from a conflicting direction whose goal is to cross the intersection; other road users are not considered.

This section further explains the interaction environment, model implementation, pedestrian behavior modeling, different experiment cases, and observables in the simulation.

### 4.1. Interaction environment

An unmarked intersection is set up in SUMO as shown in Fig. 5. The length of the lane on which vehicle moves, from the start of the lane to the intersection, is 200 m in this experiment. The pedestrian lane is meeting at the intersection which is orthogonal to the vehicle lane.

The vehicle and pedestrian behavior is modeled as a free flow. For this experiment, a flow of vehicles at the rate of 1200 vehicles/h is generated in SUMO. This flow is by default binomially distributed, approximating a Poisson distribution.

### 4.2. Negotiation model

The vehicle starts accelerating from a zero speed at the start of the lane and achieves a maximum speed at a distance of about 100 m from the intersection. The parameters recorded at each simulation step are speed and position of the vehicle and pedestrian, along with their respective distances from both lane center and curbside. The risk to each pedestrian in the scene is also computed at each simulation step. Also, the behavior type of the pedestrian is recorded which is discussed in Section 4.4. The interaction starts, and the negotiation workflow applies when the pedestrian's risk becomes greater than zero.

### 4.3. Base model for comparison

The performance of the proposed model is compared to the conservative behavior model in which a vehicle always yields to the

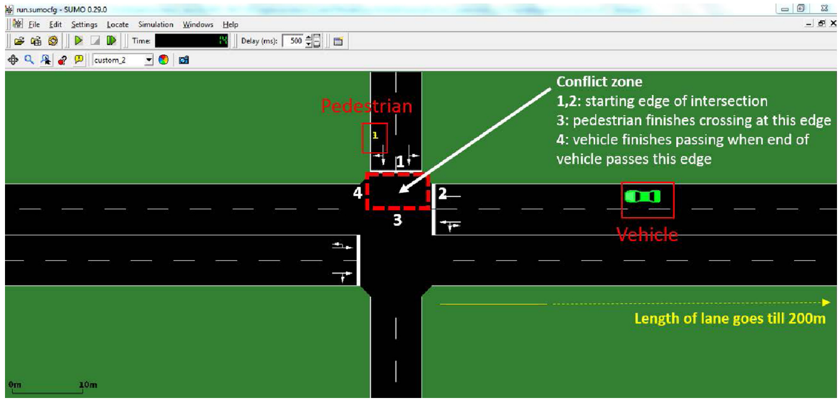



**Fig. 5.** The interaction environment setup in SUMO. This is a zoomed view of the scene. The lane actually starts from a distance of 200 m from the right.

approaching pedestrians. In implementation of this model, the vehicle prepares to stop whenever a pedestrian is detected within 2 m from the curbside.[7] The pedestrians keep on moving with the average walking speed, and the vehicle(s) waits until the pedestrians have finished crossing.

### 4.4. Pedestrian behavior modeling

The pedestrian flow is generated by introducing pedestrians in the simulation environment at different timestamps. Every pedestrian starts walking from a random distance from the conflict point with an assumed average speed of 1 m/s. Also, the waiting time limit for each pedestrian is randomly chosen from a normal distribution with mean waiting time of 20 s and standard deviation 3.33 s (reasons already discussed in Section 3.2). The following two types of pedestrian flow are generated for different experiments:

(a) *Pedestrian high-frequency (PHF)*: The pedestrian flow, in this case, is generated by varying the pedestrian rate of appearance in the simulation between 1 s and 10 s. With this frequency, the negotiation model is tested by vehicles' interaction with a total of 4382 pedestrians at the end of the simulation.
(b) *Pedestrian low-frequency (PLF)*: In another experiment, the pedestrian appearance in the simulation is randomly assigned between 1 s and 20 s, generating a total of 2273 pedestrians.

The detection and perception of a pedestrian's communication, such as gaze and gestures, cannot be modeled in SUMO. As such, the intention (and behavior) estimation step is only conceptually discussed as a part of this negotiation model, but this process is not simulated. In a real-world implementation of this model, the human behavior prediction algorithms will predict the behavior of pedestrians, which is out of the scope of this work.

Rather, the vehicle's understanding of the pedestrian behavior (*RA* or *RT*) is modeled by associating a binary value with each pedestrian ($RA = 1$, $RT = 0$). The experiment cases with different distributions of *RA* and *RT* in a pedestrian flow are discussed in the next section.

### 4.5. Experiment cases

The cases for different distributions of risk-averse (*RA*) and risk-taking (*RT*) pedestrians are as follows:

1. *With 80% risk-averse pedestrians (**RA80**)*: In simulations, the pedestrian flow is generated by assigning the risk-averse (*RA*) behavior to a pedestrian with a probability of 0.8, and a risk-taking (*RT*) behavior with a probability of 0.2. Thus, there are 80% chances that a vehicle will encounter a risk-averse pedestrian, while only 20% chances of encountering a risk-taker.
2. *With 50% risk-averse pedestrians (**RA50**)*: Here the probability of assigning a risk-averse (*RA*) or risk-taking (*RT*) behavior to a pedestrian is 0.5 each in the simulation.
3. *With 20% risk-averse pedestrians (**RA20**)*: In this case the probability of assigning the risk-averse (*RA*) behavior to a pedestrian is reduced to 0.2 while the probability of assigning a risk-taking (*RT*) behavior is increased to 0.8.

Each of the above cases with different frequencies of pedestrian flow forms six different experiment cases, represented as following- ***PHF-RA80***, ***PHF-RA50***, ***PHF-RA20***, ***PLF-RA80***, ***PLF-RA50***, and ***PLF-RA20***. The performance of the proposed model is tested for these six experiment cases against the conservative model.

### 4.6. Observables

The timestamps at which a vehicle enters the simulation environment (entry) and crosses the end of the intersection (exit) are recorded for each vehicle. Similarly, the entry and exit timestamps of each pedestrian are also recorded. The difference between the entry and exit timestamps provides the *travel or walking time* for each vehicle and pedestrian respectively. The following parameters are observed for each experiment case at the end of the simulation:

1. *Waiting time of each vehicle*: For each vehicle, the waiting time in both models is computed as the difference between the observed travel time of the vehicle, and its travel time without encountering any pedestrians.
2. *Waiting time of each pedestrian*: Similarly for each pedestrian in the negotiation model, the waiting time is computed as the difference between the observed walking time of the pedestrian, and their travel time when there are no interruptions. There is no waiting for pedestrians in the conservative model.
3. *Intersection throughput*: The intersection throughput is defined as the number of vehicles passing the conflict point per hour. The overall throughput is computed by dividing the total number of passed vehicles at the end of the simulation, by the total simulation run time.

## 5. Results and discussions

Two types of analysis were performed: *waiting time analysis of vehicles and pedestrians* and overall intersection throughput analysis. The different experiment cases in the *negotiation model (NM)* are compared

[7] The arbitrary threshold of 2 m is an assumption in the simulation, where pedestrians only move in order to cross the street; it is not intended to state that real-world vehicles apply this threshold.

**Table 2**
The vehicles' waiting times statistics (in s) for different experiment cases.

| | PHF-RA20 | PHF-RA50 | PHF-RA80 | CM-PHF | PLF-RA20 | PLF-RA50 | PLF-RA80 | CM-PLF |
|---|---|---|---|---|---|---|---|---|
| Mean/SD | 44.32/57.40 | 4.23/7.85 | 0.95/1.52 | 95.32/14.34 | 3.83/10.23 | 1.32/2.54 | 0.71/1.09 | 28.79/9.98 |
| Median | 20 | 1 | 1 | 95 | 1 | 1 | 0 | 29 |
| Mode | 0 | 0 | 0 | 99 | 0 | 0 | 0 | 31 |

to the results of *conservative model (CM)*.

### 5.1. Waiting time analysis of vehicles

The average waiting time of vehicles is computed at the end of each simulation run in each case. Next, the histogram representations are used to assess the central tendency and variability of the waiting time distributions. Lastly, a cumulative distribution graph of waiting times is discussed and compared among different experiment cases.

*Waiting time statistics*. The waiting time statistics are recorded below in Table 2. The results show that the average waiting time of vehicles in NM is significantly lower compared to the CM. For high pedestrian frequency with 20% risk-averse pedestrians (case *PHF-RA20*), the average waiting time of vehicles is 44.3 s, compared to an average waiting time of 95.3 s for conservative vehicles. In this case, 50% of the total negotiating vehicles are delayed by less than 20 s, while most of the conservative vehicles experienced a delay of 99 s. Moreover, the negotiations have further reduced the average waiting times to 4.2 s and 0.9 s in the presence of more risk-averse pedestrians (cases *PHF-RA50* and *PHF-RA80*, respectively). Even for a low pedestrian frequency, the NM performs better with an average waiting time of less than 4 s compared to 28.7 s in CM.

Furthermore, the distributions in CM (in both high and low pedestrian frequency experiments), are close to a normal distribution centered around the mean waiting time as discussed above in the respective cases (Fig. 6d and h). However in NM, the histogram plots of the waiting times of vehicles reveal a right-skewed distribution for all experiment cases (Fig. 6a–c and e–g). The right tails of these distributions suggest that a few vehicles are long delayed compared to others. The number of such vehicles with large waiting times is more in case of high pedestrian frequency compared to cases with lower pedestrian frequency.

*Cumulative distribution function (CDF) graph*. The waiting time pattern in the corresponding cumulative distribution graphs (Fig. 7) is more interpretable. It can be observed that few negotiating vehicles (case *PHF-RA20*) waited longer than the conservative vehicles ($>$ 200s). This is a result of the accumulation of waiting pedestrians for a long time before they exceeded their waiting limits and started crossing. Another reason is the waiting pedestrians' tendency to follow a risk-taker, so frequent encounters with a risk-taker are also causing few vehicles to wait longer. In such situations, the temporal gap between arrival times of pedestrians decreases and the chances of risk-taking behavior among pedestrians increases. In these cases, the vehicles have to wait longer for a negotiation opportunity.

*Frequency distribution*. The above results suggest that behavior of pedestrians and their frequency of appearance had a significant impact on the vehicles' waiting times. This is also supported by the quantitative analysis of waiting time distributions presented in Tables 3 and 4. The results suggest that if the chances of encountering a risk-averse or risk-taker pedestrian are equal (case *PHF-RA50*), then negotiations can reduce the waiting times up to 20 s for 95% of the traffic. On the other hand, when the vehicle encountered risk-taking pedestrians frequently (which is case *PHF-RA20* here) then around 30% of the total vehicles waited for more than 100 s. However, the reduced waiting times for other 70% vehicles is a result of vehicles' negotiation achieved with fewer (in this case 20%) risk-averse pedestrians.

This table shows that even fewer successful negotiation opportunities for the vehicles would allow the frequent release of vehicles through the intersection, thus reducing the possible congestion on roads. In contrast, the conservative vehicles have to wait until a safe

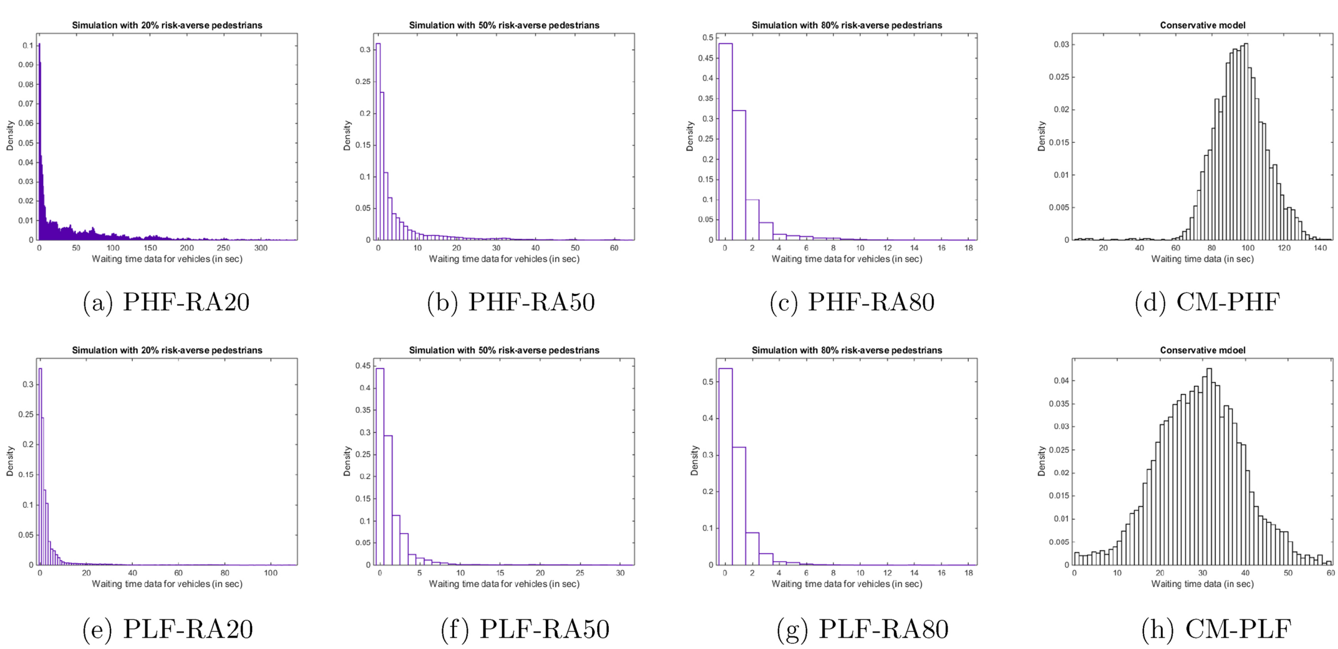
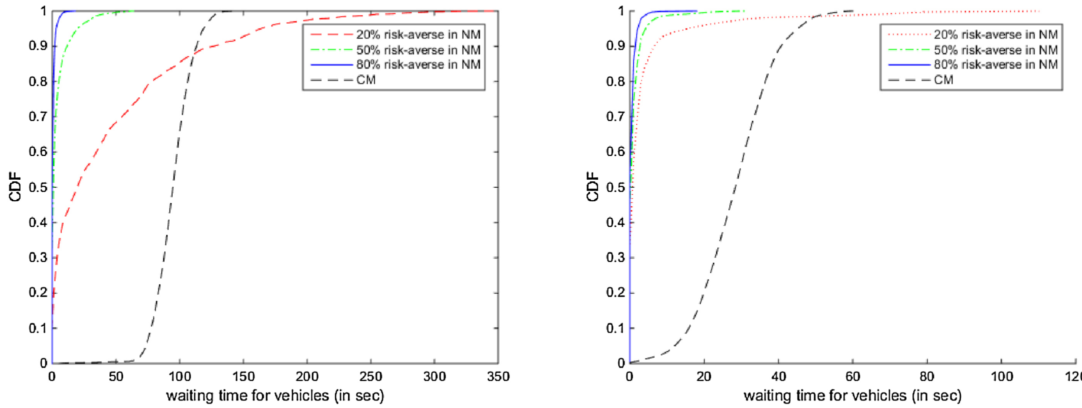



**Fig. 6.** Density graph for the waiting time data of vehicles recorded in different experiment cases in the negotiation model (a–c, e–g), and in the conservative model (d, h).




(a) High pedestrian frequency (PHF) (b) Low pedestrian frequency (LHF)

**Fig. 7.** Cumulative distribution function (CDF) graph for waiting times of vehicles in different experiment cases.

**Table 3**
Waiting time frequency distribution of vehicles for different experiment cases when pedestrian frequency is high.

| | 0 s | < 10 s | < 20 s | < 50 s | < 100 s | < 200 s | < 300 s |
|---|---|---|---|---|---|---|---|
| PHF-RA20 | 10.11% | 31.39% | 8.89% | 17.94% | 17.04% | 11.99% | 2.64% |
| PHF-RA50 | 31.05% | 57.68% | 6.37% | 4.54% | 0.35% | 0% | 0% |
| PHF-RA80 | 48.64% | 51.10% | 0.25% | 0% | 0% | 0% | 0% |
| CM | 0% | 0.11% | 0.09% | 0.30% | 65.11% | 34.39% | 0% |

**Table 4**
Waiting time distribution of vehicles for different experiment cases when pedestrian frequency is low.

| | 0 s | < 10 s | < 20 s | < 50 s | < 100 s | < 200 s | < 300 s |
|---|---|---|---|---|---|---|---|
| PLF-RA20 | 32.66% | 60.65% | 2.62% | 2.55% | 1.40% | 0.11% | 0% |
| PLF-RA50 | 44.46% | 54.27% | 0.83% | 0.44% | 0% | 0% | 0% |
| PLF-RA80 | 53.65% | 46.27% | 0.09% | 0% | 0% | 0% | 0% |
| CM | 0.28% | 3.02% | 17.04% | 78.14% | 1.53% | 0% | 0% |

gap from the pedestrians is identified which leads to traffic congestion when the frequency of pedestrians is high. Also, the overall traffic movement is improved through negotiations with reduced waiting time for vehicles, compared to the conservative model.

### 5.2. Waiting time analysis of pedestrians

The reduced waiting time for vehicles in NM is at the cost of some waiting time for pedestrians which is discussed in this section. Similar to the previous analysis of vehicle waiting times, the following section discusses the average waiting times of pedestrians, and also a comparison of their distributions in different cases.

*Waiting time statistics*. The waiting time statistics for pedestrians are recorded in Table 5. In case of simulation with 80% risk-averse pedestrians, their average waiting time is 13.2 s. It shows that a risk-averse pedestrian is most likely to wait for not more than 14 s. This number is even less than the pedestrians' intended average waiting times observed in various empirical studies (Li, 2013; Kaiser, 1994) on pedestrian behaviors. Moreover, their waiting time is significantly less compared to the waiting time of vehicles. Thus, the pedestrians' compromise on waiting times during negotiations can reduce the future traffic congestion problems, also increasing their coordination with self-driving vehicles on roads.

*Frequency distributions and CDF*. The pedestrians' waiting time distributions (Fig. 8) further reveal the movement patterns of vehicles and pedestrians. The peaks of the extremely right-skewed distributions in Fig. 8a and c show that most of the pedestrians (risk-takers) crossed the intersection without waiting. While in cases of 50% likelihood of risk-taking behavior Fig. 8b and d, the occurrences at longer waiting times show the successful negotiation by vehicles which improved the traffic flow.

However, experiments with 80% risk-averse pedestrians reveal a random distribution of waiting times with few higher peaks around their waiting time limit of 20 s (Fig. 8c and f). The cumulative distribution graph for these waiting times is shown in Fig. 9. The jump in CDF around 20 s waiting time (Fig. 9b) suggests the case of accumulation of risk-averse pedestrians for a long time which makes them impatient. This confirms the discussion on patterns observed in vehicles' waiting time distributions where few vehicles have to wait much longer until the next negotiation opportunity. This shows that negotiations allow the frequent release of traffic from both sides – vehicles and pedestrians, thus reducing the chances of congestion as compared to CM.

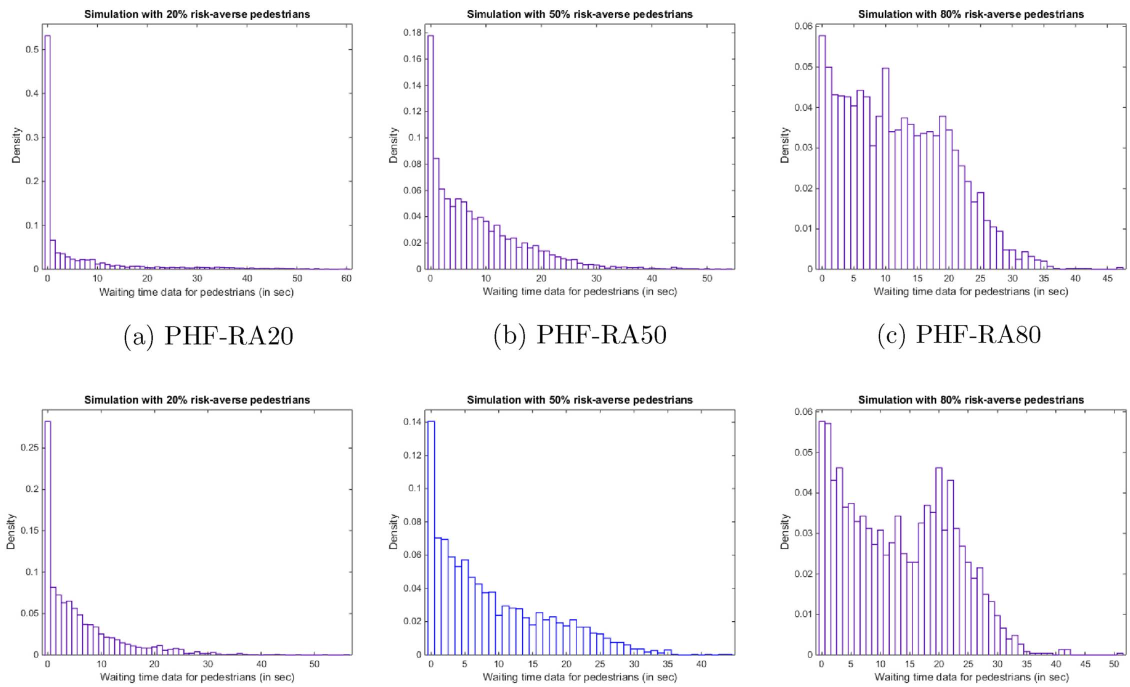
### 5.3. Throughput analysis

The intersection throughputs for different experiment cases are presented in Table 6. In the NM, except for the case with fewer risk-averse pedestrians (*PHF-RA20*), in other cases, almost all the vehicles that were introduced in the simulation passed (*throughput* ≈ 1200 vehicles/h). For high pedestrian frequency and more risk-takers in the scene, the throughput in NM is reduced to 70%.

The NM performs better compared to the conservative model in which only 659 vehicles were able to pass (about 50% of the throughput in negotiation model). While in case of low pedestrian

**Table 5**
The pedestrians' waiting times statistics (in sec) for different experiment cases.

| | PHF-RA20 | PHF-RA50 | PHF-RA80 | PLF-RA20 | PLF-RA50 | PLF-RA80 | CM |
|---|---|---|---|---|---|---|---|
| Mean/SD | 5.86/10.84 | 8.23/8.43 | 11.93/8.31 | 6.01/7.49 | 9.13/8.46 | 13.28/9.26 | 0 |
| Median | 0 | 6 | 11 | 4 | 7 | 13 | 0 |
| Mode | 0 | 0 | 0 | 0 | 0 | 0 | 0 |




(a) PHF-RA20 (b) PHF-RA50 (c) PHF-RA80

(d) PLF-RA20 (e) PLF-RA50 (f) PLF-RA80

**Fig. 8.** Density graph for the waiting time data of pedestrians recorded in different experiment cases.

frequency the throughput for both models is the same and almost equal to the regular vehicle flow. It is clear then that more vehicles are passing through the intersection in the NM, which supports the hypothesis.

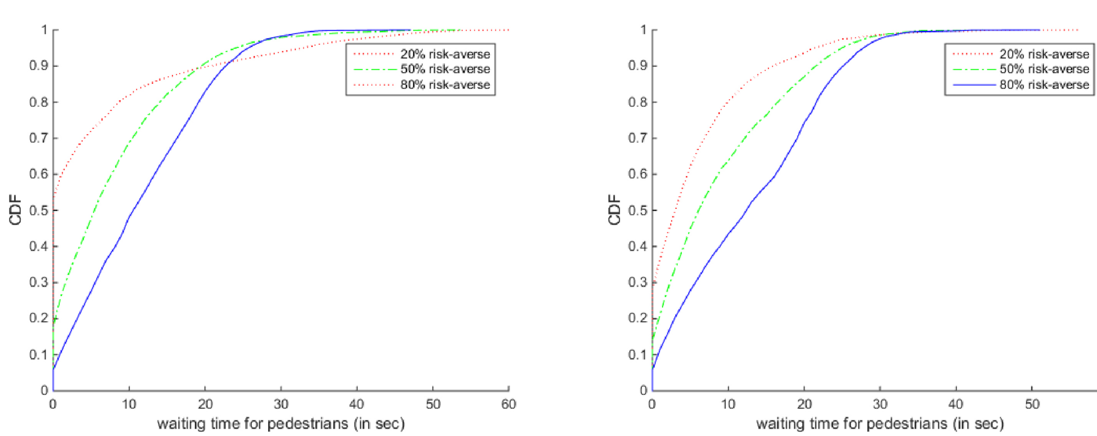
## 6. Conclusions

Existing studies concerning the interaction of vehicles and pedestrians are limited to human behavioral psychology, to algorithms for the pedestrian intention recognition, and to understand pedestrians' trust toward future self-driving vehicles. This paper, however, is an attempt to describe another aspect of traffic behavior – *right-of-way negotiations* among vehicles and pedestrians. This paper extends the prior model of physical constraints and allows vehicles to negotiate with multiple pedestrians considering also social rules in making individual decisions. It also includes different personalities in terms of risk-taking behavior, which are included in the social rules. This paper demonstrates negotiation by vehicles with a mix population of risk-averse and risk-taking pedestrians, without compromising pedestrians' safety. The model is realized through simulations using SUMO and MATLAB. This work builds on a previous negotiation model for single vehicle–single pedestrian interactions that introduced social rules. The extensions of the model presented in this paper allow for multiple vehicle–pedestrian interactions with individual decision-making and include risk-taking attitudes of individuals.

**Table 6**
Intersection throughput (vehicles/h) for different experiment cases.

| PHF-RA20 | PHF-RA50 | PHF-RA80 | CM-PHF | PLF-RA20 | PLF-RA50 | PLF-RA80 | CM-PLF |
|---|---|---|---|---|---|---|---|
| 857 | 1189 | 1195 | 659 | 1180 | 1194 | 1195 | 1139 |

The simulation results show that negotiations reduce the waiting time for vehicles at intersections at the cost of some waiting time for pedestrians, resulting in a smooth flow of traffic. This supports the hypothesis of this study. However, the pedestrian waiting times are not




(a) High pedestrian frequency (PHF) (b) Low pedestrian frequency (LHF)

**Fig. 9.** Cumulative distribution function (CDF) graph for waiting time of pedestrians in different experiment cases.

longer than their maximum waiting time limits observed in existing empirical studies. This indicates that in the future, negotiation is a solution to the estimated congestion problem due to expected conservative behavior of current self-driving vehicles. The other socioeconomic benefits of traffic negotiations include lower emissions and reduced health hazard risks, contributing to a more liveable community.

However, the model presented here is subjected to a few environment and technology constraints and in the future, there is still a scope to improvise the model considering more realistic scenarios. This study is currently restricted to vehicles and pedestrians moving in a fixed direction, and the road design factors around intersections are not considered in this work. Negotiations will become complex when there is an influence of traffic from other directions. More issues include the unpredictability of pedestrian behavior and the influence of local norms in their behavior. Some road users can more easily change their behavior at the last minute. Also, the level of commitment to a given behavior matters. From the pedestrians' point of view, there could be a problem of perception or comprehension of future vehicle's intentions. Also, the above results may vary in real-life settings as it is difficult to determine the road users' accurate behavior in any situation. The future work will focus on some of these issues, depending on the feasibility of experiments.

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