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Part II

Traffic Management Using Risk Limits
Chapter 4

Risk Limit Model

In this chapter we introduce a model for traffic management centred around the concept of a risk limit, which represents an acceptable level of accident risk that vehicles must not exceed. This model aims to facilitate dynamic, online traffic management, in which vehicles continually assess the current situation they are in and respond accordingly. In order for such a system to be possible, it is necessary to have both computational power in each vehicle and communications capabilities between vehicles.

I will first provide an overview of the risk limit model before going into more detail on each of its stages: determining risk, including a discussion of risk factors and how to use them in the model; the risk limit itself; and vehicle behaviour. In particular, we will look more closely at one vehicle behaviour, link choice, and how it can be adapted to include consideration of overall system utility, as well as each vehicle’s individual self-interest, by the use of a social link choice algorithm.

4.1 Model Overview

The aim of this model is to be able to maintain a given accident rate whilst maximising utility. Risk mitigation measures are adapted to the current situation, rather than having static risk mitigation measures in place at all times. By adapting vehicle behaviour in situations in which risk is low we can improve utility, without compromising safety in situations where risk is high.

We define accident risk as the relative difference in the probability of being involved
in a collision. That is, we take a risk value of 1.0 to represent the base accident probability in the absence of any factors which either increase or decrease risk. This does not represent a realistic scenario, since some risk factors will always be in effect, however, it is a means of comparing and combining the effects of different risk factors. Accident risk is often formulated to include a measure of the severity of the accident, usually in terms of harm to vehicle occupants. We are primarily concerned with the accident rate, that is, the number of collisions occurring per unit time, as this is the aspect of accident risk that is most amenable to mitigation by dynamic modification to vehicle behaviour. Thus we do not include the severity of potential accidents in the definition of risk; it refers only to the likelihood of a collision occurring.

Each risk factor is then considered to have an effect relative to the base risk level of 1.0. A factor which doubles the likelihood of an accident, for instance, would represent a risk level of 2.0, while one that halves the likelihood would have a risk level of 0.5. Combining risk factors to get a measure of overall risk at a given time is a complex problem in itself, largely because there is a scarcity of data on many risk factors and many of them are difficult to model. It is important, therefore, that when factors are incorporated into this model, especially when it is expanded to include many different factors, careful consideration is given to how the factors are combined, with particular attention paid to possible interactions between factors.

We have thus far only employed a limited number of factors at a time and are also limited by the available data on risk factor interactions. Furthermore, we aim to initially produce a model that is simple to implement and study as we are more focused on the overall effects of using a risk-limit based system on accident rate and utility. As such, here we simply take the mean of any risk factors in effect to get an approximation of the overall risk level. In future iterations of the model this may be improved in favour of a more complex risk factor combination method.

A diagram of the algorithm for traffic management using risk limits is given in Figure 4.1. Each vehicle first calculates its current risk level by combining its risk factors. These may be factors relating to the driver, the vehicle, or the surrounding environment. This value is then compared to the risk limit. If the current risk level is above the risk limit, the vehicle must take risk-mitigating behaviours. If the current risk level is below the risk limit, the vehicle may take utility-increasing behaviours.
4.1. MODEL OVERVIEW

Figure 4.1: A model for traffic management based on the concept of risk limits. Vehicles first determine their level of risk by combining any risk factors currently in effect. This value is then compared to the risk limit. If the vehicle’s risk is above the risk limit, it must take risk-mitigating behaviours to reduce its risk. If its risk value is below the limit, it can instead take utility-increasing behaviours.
4.2 Determining Risk Level

In order to use a risk limit, we need to know whether we are conforming to it. To do this, we need to determine the current level of risk in order to make a comparison to the desired value, i.e. the risk limit. This consists of identifying risk factors that are currently in effect, determining to what extent they are affecting the current risk level and combining them to get an estimate of the overall risk at the current time.

4.2.1 Risk Factors

Section 3.1 gives an overview of existing research into accident risk. In order to create a risk mode, it is important to be able to compare vehicles or situations with and without the risk factor in question. For example, it would not be helpful to know that 20% of accidents involve sports cars if we do not also know many sports cars are not involved in accidents, or what the total incidence of sports cars on the road is. For this reason, comparative studies are needed which demonstrate accident risk of a certain amount above or below what it would be without the factor being present, or that include some measure of exposure to risk in addition to the actual accident rate. Most traffic authority databases record only vehicles that were involved in accidents, with little information available about the overall prevalence of vehicles with the factors in question.

There are a number of possible methodologies to overcome this limitation. One is to use records of licence holders or registered vehicles, or similar statistics, in order to get an overall measure of exposure. However, this only applies to a limited set of factors (those for which such information is available) and acts on a very broad basis — there might be, for instance, data on an entire age range for drivers, or on all vehicles of a particular type. This information typically gives no insight into the driving habits of the drivers or vehicles in question, such as which drivers travel more hours per year, or which vehicles are more likely to travel on which types of roads. Moreover, when attempting to combine multiple factors from such data, the factors will often not be independent and so a naive combination of their effects on risk will be inaccurate.

One of the most accurate means of determining exposure lies in on-road surveys, however the cost of these is usually prohibitive and so studies employing this methodology are limited in number. A more feasible methodology in many cases is to use induced exposure [54, 55]. This is a means of determining exposure from the detailed,
numerous and more readily available data contained in traffic authority crash databases. In this method, an estimate is made of the total proportion of vehicles on the road matching a particular factor by dividing vehicles involved in accidents into those that are considered at-fault, or at least partly responsible for the accident, and those that are not. For instance, in a single-vehicle accident, that one vehicle is considered entirely at fault, while in a multi-vehicle accident, the first two vehicles to collide may be considered responsible.

This methodology has a number of limitations as it does not take into account possibilities such as a vehicle being forced off the road by another vehicle which was not then involved in the accident, or collisions between vehicles in which one vehicle is entirely at fault. Some refinements can be made to account for this, for instance, by separating out rear-end collisions versus frontal collisions, but in the end the measure of exposure will still only be approximate. However, this method has the significant advantage of being quick and cost-effective to implement.

Even where the effects of risk factors have been measured, problems often arise in trying to measure the presence or extent of these factors in a given situation, i.e. to test, in real-time, whether the factor is in effect and, for many factors, by how much. For vehicular factors, this may often be straightforward as we can calculate the effects of characteristics such as maximum deceleration or mass. This is also true for some environmental factors — typically those that have direct, physical effects on the vehicle. Factors relating to the driver of the vehicle, however, present significant challenges.

As discussed in Section 3.1.1, human factors account for between 65% and 75% of traffic accidents [11–13] and so are among the most important factors to include in a risk model. However, these are also often the most difficult factors to measure and test for. For some temporary human risk factors, such as driver fatigue [120] and potential distractions such as mobile phone use [121], technological advances have enabled closer monitoring of the driver in real time, which leads to a more accurate measure of these factors that does not require the active participation of the driver. When dealing with longer-term factors which may vary only over the course of months or years, however, those human factors which are relatively simple to model are also the ones least useful in determining risk. [122] found that vehicle control skills had no correlation to accident risk. This is supported by findings that professional race drivers, a highly skilled subset of the driving population, have a higher accident involvement than other drivers [123] when driving on ordinary roads. Factors relating to perception and cognition are the
best determinants of accident risk. Hazard perception [37, 122], field dependence [12, 15, 124, 125], visual impairments [14], selective attention skill [12, 17, 125] and drivers’ awareness of their own risk [12, 39, 40] have all been shown to predict accident risk.

Many of these factors have the problem that they are difficult, time-consuming or expensive to measure, often requiring extensive tests conducted by specialists. Even once measured, modelling them is a challenging task. Some attempts have been made to provide models of drivers’ perception and cognition [77, 78] and their emotions and personality [79, 80], however these models are much more complex and difficult to implement than purely physical models of vehicle dynamics such as those proposed by [82] and [83].

While these problems are substantial, it is still possible to obtain a coarse-grained estimate of the risk value by using only one or a few factors — preferably those with the biggest contribution to accident risk, although the possible factors to use also depends on the available data. Even an incomplete risk estimate can give a measure of the difference in risk between different vehicles, drivers and environments and thus can be used as a means to inform changes in vehicle behaviour for the purposes of risk mitigation. Furthermore, as risk models requiring this information are developed, this gives a motivation for the research community to obtain the needed data about individual risk factors in order to improve the exactness of the risk model.

**4.2.2 Calculating the Risk Level From Risk Factors**

We propose a model in which information about the risk factors pertinent to a vehicle is combined to give a risk value. This is done by calculating a relative value for each factor; for instance, a factor which increases risk by 50% will have a value of 1.5, a factor which causes no change in risk will have a value of 1.0 and a factor which causes a 50% reduction in risk will have a value of 0.5. The individual values for each factor are averaged together to give the overall risk value for a vehicle. This risk value can change rapidly as environmental conditions change and as other vehicles enter and leave the nearby area. This model is designed to be modular so that as risk factors are increasingly able to be understood, measured and modelled, they can be added to the model with minimal alteration to the overall algorithm.
4.3 The Risk Limit

The risk limit represents an acceptable or target level of accident risk which vehicles should not exceed. It is analogous to a speed limit; vehicles may have a risk level below the risk limit but their risk level should not go above it. In a sense, any risk mitigation strategies are attempts to bring accident risk down to a level that is considered acceptable — it is not possible to reduce the risk to zero, since there could always be some unexpected event or unforeseen circumstance, so instead we aim for a low but achievable level.

However, previous strategies for risk mitigation have been employed piecemeal, with each method assessed individually on its benefits versus its costs, both in terms of financial outlay and in terms of reduction of utility in the road system. Sometimes these methods are co-ordinated and deployed together in a consistent way — for instance, in a shared zone, several traffic-calming measures might be implemented at once and work together to achieve the overall effect of vehicles moving more slowly through the area. For long-term, static risk mitigation strategies, which typically require significant initial investment but will then be in place for some time, this methodology makes sense. Each measure is part of a long-term strategy to reduce accident risk, rather than a dynamic assessment of the current situation.

The risk limit, however, provides a unifying concept around which mitigation strategies can be organised and a useful means for determining and quantifying what level of risk mitigation is needed at any given time. As such, it provides a benchmark for dynamic risk mitigation, in which particular risk-mitigating behaviours may be adopted, dropped, or varied on an ad-hoc and rapidly changing basis. In order to quickly make decisions about which behaviours to employ, it is necessary to know the effects of those behaviours, and the effect, in terms of risk reduction, that is needed at any given time, so that behaviours can be matched to the current situation.

In this way, in this model, the risk limit is intimately tied to both determining the current risk level and to vehicle behaviours. The aim of determining the risk level is so that it can be compared to the risk limit in order to get a measure of the reduction in risk that is required, or, conversely, the available leeway for increasing utility if the risk level is already below the limit. Similarly, vehicle behaviours are chosen in such a way as to meet the risk limit while maximising utility.
CHAPTER 4. RISK LIMIT MODEL

The risk limit also provides a means for calibrating the overall management of traffic. A traffic authority may determine a risk limit suitable for the region over which they have control. This might be based upon existing accident rates, or perhaps on a target rate that the authority is attempting to reach by employing the risk limit model. Setting the risk limit could also be approached from the perspective of utility: if a particular level of utility is required, what risk level must be allowed to achieve this? A combination of these two approaches could also be used, and where there is a conflict between the level of accident risk considered acceptable and the level of utility desired, this may be used to inform work to improve risk mitigation and/or utility maximisation methods, as it would provide a concrete target to aim for.

4.4 Vehicle Behaviour

Vehicle behaviours used in the risk limit model fall into two categories — risk-mitigating behaviours and utility-increasing behaviours — although in many cases, these will be directly and inversely related. For instance, varying speed affects both utility and risk level, so decreasing speed may be a risk-mitigating behaviour whilst increasing speed may be a utility-increasing behaviour. Similar effects can be seen for headway, lane choice and link choice — all behaviours that affect both utility and risk. This is a consequence of attempting to balance and find a suitable trade-off between risk and utility. If a behaviour only increases utility or only decreases risk, without affecting the other, there is no reason not to employ this behaviour all of the time (unless it has costs that are not currently included in this model, such as financial costs). Thus when we modify vehicle behaviour to meet the risk limit whilst maximising utility, we naturally focus on behaviours that affect both these measures.

Choosing vehicle behaviours to mitigate risk is closely related to determining risk in the first place. As with determining risk, it is not enough to know simply that a behaviour reduces risk, we must know by how much it does so in order for it to be effectively employed and in order to know that we are indeed meeting the risk limit. Since many behaviours are directly tied to particular risk factors — for instance, we can consider speed as a risk factor, but setting the current speed is also a behaviour a vehicle can employ — we can use many of the same techniques discussed in Section 4.2 in order to quantify the effects of these behaviours and use them in the model. Essentially, then,
4.4. VEHICLE BEHAVIOUR

A risk-mitigating behaviour is a risk factor over which the vehicle or driver has some measure of control.

We can consider two types of risk-mitigating behaviours: those that are discrete (i.e. one chooses from a finite set of alternatives) and those that vary continuously (one may take any desired value for that behaviour). An example of the former would be link choice: we choose to travel on either link A or link B; we cannot travel partially on both at the same time. Decreasing speed is an example of the latter; we may decrease our speed by a small amount, a large amount, or even negatively — i.e. increase our speed — which would then have a detrimental effect on risk.

In the discrete case, the set of available choices will have different effects on both utility and risk. In order to keep to the risk limit, we must always take a choice that does not bring our current risk level above it. However, within this bound, we are free to choose the best option from a utility standpoint. It may also be the case that there are choices that are completely dominated by other choices — that is, there exists a choice that is better in terms of both risk level and utility. An example of this may be a winding mountain road that is both risky and slow. These choices would then typically not be taken until conditions change to make them viable again.

For continuous behaviours, we are free to set exactly the level of risk mitigation that is required. That is, we set the value of the behaviour to be at the best utility possible without exceeding the risk limit. Continuous behaviours such as speed or headway thus give us more flexibility in maximising utility whilst meeting the risk limit and as such can in some cases be used to compensate for a poor selection of discrete behaviours. For instance, if all available links place us well below the risk limit, we can increase speed and/or decrease headway until we are once again close to the risk limit, thus improving our utility. Or conversely, if our only choices are too risky, we may decrease speed or increase headway, thus reducing our utility, in order to compensate and be able to take an option that is otherwise unavailable whilst staying at or below the risk limit.

This model is intended to be generic and modular, so that as new vehicle behaviours are able to be understood, measured and modelled, they can be added to the model with minimal alteration to the overall algorithm. The vehicle or driver is free to choose whichever combination of behaviours they desire, so long as the risk limit is met. It is understood, however, that the goal of a vehicle or driver is always to maximise utility, and that behaviours will be chosen accordingly. In this work, we take a relatively narrow definition of utility as relating only to the efficiency of the road system. In reality,
drivers may have other concerns such as economic costs, a wish to take a scenic route in order to enjoy the view, or a preference for a route that is more familiar, even if it is not optimal. These considerations are, however, beyond the scope of this work.

4.4.1 Risk-Aware Link Choice

One example of vehicle behaviour that can be used to mitigate risk is route choice and we will now extend the risk limit model to include link choice as a first step towards incorporating end-to-end route choice. Route choice has a significant bearing on accident risk. Road type, intersections, geometry and other features all contribute to accident risk [32, 33] and can be partially or totally controlled by a driver’s choice of route. When taking route decisions, drivers have been shown to adjust their choices in response to perceived accident risk [126, 127].

As a discrete behaviour, link choice presents challenges that do not apply to continuous behaviours such as speed or headway. A vehicle is only able to choose amongst the currently available options, rather than setting an optimal value for risk mitigation for itself. The approach taken here to manage this task of choosing one of a finite set of options can potentially also be applied to other discrete behaviours as they are added to the risk limit model in future.

In order to make risk-aware link choices, vehicles choose links that provide the current maximal utility, based on information received from other vehicles and/or roadside base stations, while adjusting other behaviours, primarily speed, to remain within the risk limit. In this way, the risk associated with choosing a particular link is directly related to that link’s utility — a riskier link will require a vehicle to travel more slowly, or else employ other risk-mitigating behaviours, in order to maintain a sufficiently low risk level, and the converse is true for a less risky link. Here we do not consider overall route choice, only incorporating risk when choosing amongst links that are equally useful or valid in reaching a vehicle’s destination. However, Section 10.2.1 discusses how this might be extended to include risk in end-to-end route choices.

To include accident risk in vehicle link choices, we first need to assign a risk value to each link. This can be calculated by combining any relevant risk factors that apply specifically to the link, such as the road type, condition and geometry, the surrounding environment (e.g. whether it is urban, suburban or rural; the presence of hazards such as cliffs; or whether animals are likely to walk onto the road), and features such as
4.4. VEHICLE BEHAVIOUR

intersections. However, since we are here concerned with examining vehicle link choice in the presence of links of different risk levels, we take the link risk as an independent variable and simply assign each link a value.

As a vehicle approaches an intersection, it uses the risk values for each link it can choose to determine what its risk level would be if it were travelling on that link. We give the vehicle risk and link risk equal weighting, so to determine a vehicle’s risk level on a given link, we take the average of the vehicle risk and the link risk

\[ r = \frac{r_v + r_l}{2} \]  

(4.1)

where \( r \) is the vehicle’s overall risk level if it chooses the link in question, \( r_v \) is the risk for the vehicle and \( r_l \) is the risk for the link. Taking the average of these two values maintains the previous definition of risk discussed in Section 4.1.

In reality, both the vehicle risk and the link risk would be a combination of multiple factors, with the vehicle risk incorporating factors relating not only to the vehicle itself, but also to the driver. As such they would not be likely to have equal weight in calculating the total risk, however since here we are considering both vehicle risk and link risk as independent variables which may vary arbitrarily, and since we use only these two parameters to represent the aggregates of many factors, varying the weightings is equivalent to varying the values themselves and thus unnecessary. In reality the vehicle and link risk would instead consist of multiple individual risk factors, however this is not required in order to develop an algorithm for risk-aware link choice, so we use this simplification as a stand-in for the full model. The key point is that the vehicle must determine what its risk value would become if it were to take the link.

This then allows the vehicle to determine the maximum speed it can travel on that link whilst maintaining the risk limit. We will refer to this speed as vehicle maximum speed (for a given link). If there are other vehicles already on the link, it is possible the vehicle will not actually be able to reach its allowed maximum speed, however. For this reason, the vehicle also calculates the maximum speed it would be possible to travel on the link. We will refer to this speed as link maximum speed (which varies over time as traffic conditions on the link change). To calculate the link maximum speed, we use the current speeds of vehicles on the link and their positions along the link. This is to account for vehicles that, while slow, may be close to the end of the link and thus have little impact on the maximum speed possible on the link.
To do this, we consider each lane on the link separately. In each lane, the speed and position of the last vehicle on the link are used to calculate the time it will take this vehicle to reach the end of the link. The total length of the link is then divided by this time to give the maximum possible average travel speed for that lane without colliding with preceding vehicles. This process is repeated for each lane and the highest resulting speed is taken as the overall maximum speed for the link. In the case where there is at least one lane with no vehicles in it, the maximum speed for the link is infinity. This is not a perfect measure as it does not take into account vehicle headway or the possibility that vehicles will change lanes or speed before the vehicle doing the calculation actually reaches them. However, this level of detail is sufficient for choosing amongst links and is relatively fast to calculate.

The vehicle then takes the minimum of the speeds it has calculated — the vehicle maximum speed for the link, and the link maximum speed at that point in time — in order to obtain the resulting overall highest speed for that link. We will call this speed the effective speed for that vehicle and link. Once the vehicle has calculated its effective speed for each link, it can compare these to find the link with the highest effective speed and choose that as its next link. See Figure 4.2 for a summary of this algorithm.

Using this algorithm, each vehicle chooses the best link based on its own risk, the link risk, and the current traffic situation. Initially, vehicles will favour the link with the lowest risk as it allows them to travel at higher speeds. However, as this link becomes congested, its current travel speed will drop, causing vehicles to choose other links. Additionally, if a high risk vehicle is already travelling (slowly) on the “fastest” (lowest risk) link, other, lower risk vehicles may choose a higher risk link since although their own maximum speed on this link would be lower, the current travel speed may be higher, making it the better choice. The combination of these processes means that traffic load between the links is dynamically balanced in a distributed, emergent fashion that takes into account link risk and compensates for it.

4.4.2 Social Link Choice

It is important to also consider the effect a vehicle’s link choice has on the utility of other vehicles. When a vehicle takes a risk-mitigating behaviour, such as reducing speed, as a result of its link choice, this negatively impacts on the vehicles following it, particularly in the case of single-lane links. To deal with this, we add a social penalty for reducing
4.4. VEHICLE BEHAVIOUR

Figure 4.2: An algorithm for risk-aware link choice. The vehicle calculates the risk value it would have if it were to travel on each of the available links. From this, it can determine the maximum speed it may travel on each link whilst maintaining the risk limit. It then compares this to the link speeds as constrained by other vehicles to obtain an overall speed for each link, and chooses the link with the highest speed.
CHAPTER 4. RISK LIMIT MODEL

<table>
<thead>
<tr>
<th>Link</th>
<th>Link risk</th>
<th>Maximum speed (m/s)</th>
<th>Current link maximum speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>16.09</td>
<td>18.0</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>13.33</td>
<td>14.0</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>11.45</td>
<td>11.6</td>
</tr>
</tbody>
</table>

Table 4.1: Maximum speed vehicle A can travel on each link.

utility of other vehicles and investigate the effects of including this penalty as a factor in vehicles' link choices.

4.4.2.1 Motivation

Since different vehicles have different risk values, their maximum travel speeds on a given link will also differ. This means that it is possible for a vehicle's maximum speed to be lower than the current speed for a given link, but for that link to nonetheless be its preferred link. Figure 4.3 gives an example of such a scenario. All maximum speeds used here are calculated from the maximum speed function determined in Section 6.2, however, it is not critical for this example to be familiar with this function.

Vehicle A, with a risk value of 1.5, is approaching the intersection. Table 4.1 shows the maximum speeds for vehicle A on each of the links it can choose.

The current link maximum speeds for the links are 18.0 m/s for link 1, 14.0 m/s for link 2 and 11.6 m/s for link 3. Then vehicle A’s preferred link when it considers only its own effective speed is link 1. However, should vehicle A choose link 1, the link maximum speed for this link will be reduced to vehicle A’s maximum speed of 16.09 m/s, a reduction of 1.91 m/s (although this reduction will become less severe over time as vehicle A progresses along the link). Any following vehicles would have their speed on link 1 correspondingly reduced, until such time as vehicle A leaves the link.

However, since the current link maximum speeds for the links are different, this detrimental effect on following vehicles is not even across the links. Table 4.2 shows the slowdown caused by vehicle A choosing each of the links. We see that the smallest reduction in speed would be caused by vehicle A choosing link 3. However, this also gives vehicle A the lowest possible speed.

Values shown in this example are not unusual and as such the situation described above, in which one link would give the best speed for a vehicle, while a different link gives the lowest speed reduction for the following vehicles, is common. In the following section, we give a method for balancing the two concerns of individual vehicle speed
4.4. VEHICLE BEHAVIOUR

Figure 4.3: Vehicle A’s preferred link is link 1, however the maximum speed vehicle A can travel on this link is only 16.09 m/s, which is lower than the current link speed of 18.0 m/s.
### CHAPTER 4. RISK LIMIT MODEL

<table>
<thead>
<tr>
<th>Link</th>
<th>Current link maximum speed (m/s)</th>
<th>Vehicle maximum speed for vehicle A (m/s)</th>
<th>Speed reduction if vehicle A chooses this link (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.0</td>
<td>16.09</td>
<td>1.91</td>
</tr>
<tr>
<td>2</td>
<td>14.0</td>
<td>13.33</td>
<td>0.67</td>
</tr>
<tr>
<td>3</td>
<td>11.6</td>
<td>11.50</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 4.2: Reduction in link speed caused by vehicle A choosing each link. Vehicle A can travel fastest on link 1, however this will also cause the greatest speed reduction for other vehicles.

and speed reduction for other vehicles.

#### 4.4.2.2 Algorithm

We define a social penalty associated with each link a vehicle can choose at a given intersection. The social penalty is given by the speed reduction should that vehicle choose that link, as described above, i.e. the difference between the current link maximum speed and the vehicle maximum speed. The social penalty is always non-negative — if the speed difference is negative, the social penalty is set to zero. This is because a vehicle cannot increase the current link speed even if its vehicle maximum speed is higher, as it is still constrained by the speed of the vehicles in front of it.

The social penalty is given by

\[
p = \max\{s_l - s_v, 0\}
\]  

(4.2)

where \( p \) is the social penalty, \( s_l \) is the current link speed and \( s_v \) is the vehicle’s maximum speed for that link.

Each vehicle then calculates a score for each link based on its maximum speed for the link and the social penalty for the link.

\[
c = e_{vl} - p \times M
\]  

(4.3)

where \( c \) is the score for the link, \( e_{vl} \) is the effective speed for the vehicle on this link, \( p \) is the social penalty for the link, and \( M \) is a multiplier indicating how much weight is given to the social penalty versus the link speed.

The social penalty multiplier corresponds to how selfish a vehicle’s behaviour is. A multiplier of zero would mean a vehicle always chooses the link with the best speed.
for itself, regardless of the effect on other vehicles. Higher multipliers correspond to
greater weight given to the speed reduction for others. Note that both the effective speed
$s$ and the social penalty $p$ are in metres per second, however since one is absolute speed
while the other is a speed difference, they will typically not be close in magnitude.

In a real-world implementation of this system, traffic authorities may enforce a par-
ticular level of the social penalty multiplier or may aim to influence it if this choice is
left to the driver. This might be done by regulations, incentives to drivers, or bargaining
schemes. The aim here would be to find the best trade-off between the individual utility
of a given driver and the broader utility of all drivers collectively.
Chapter 5

Experimental Investigations

In order to test the feasibility and effectiveness of the risk limit model, each stage needed to be tested: first determining risk then using this information to modify vehicle behaviour. To investigate determining accident risk, we used accident data from the NSW CrashLink database to test how different risk factors can be evaluated and combined to give an overall measure of risk.

We then implemented the risk limit system in Paramics with a set of initial risk factors and vehicle behaviours to measure its effects on accident rate and utility. This was then further extended to include the additional vehicle behaviour of link choice and to investigate the effects of social link choice.

5.1 Calculating Risk

NSW Roads and Maritime Services collects data from traffic accidents on state roads. All accidents which result in death, injury or at least one vehicle being towed away are recorded in the CrashLink database. CrashLink is a comprehensive record of road accidents in NSW, including the characteristics of the vehicles and people involved and of the crashes themselves, such as data on location, road features, and other environmental factors relating to each crash. A section of this database was used for analysing the feasibility of calculating risk values based on risk factors. The data used was from the F3 (Sydney to Newcastle) Freeway for the years 2004 to 2008 inclusive.
5.1. CALCULATING RISK

5.1.1 Selecting Risk Factors for Analysis

Although there are a large number of parameters contained in the crash database, not all of them are suitable for calculating risk values for the purposes of modifying vehicle behaviour. While the database records the number of incidents for any given combination of factors, what is not known is the number of vehicles or drivers who share these characteristics and did not crash. That is, there is no measure of exposure or control group available from CrashLink itself. This means that it is difficult to reliably distinguish between an increased number of crashes due to a larger prevalence of a given risk factor in the general population, and an increased number of crashes due to increased accident-proneness correlating to that risk factor.

In order to gain an estimate of the proportion of the general population of drivers and vehicles that share a particular risk factor, we use induced exposure [54,55]. In this method, an estimate is made of the total proportion of vehicles on the road matching a particular factor by dividing vehicles involved in accidents into those that are considered at-fault, or at least partly responsible for the accident, and those that are not. For instance, in a single-vehicle accident, that one vehicle is considered entirely at fault, while in a multi-vehicle accident, the first two vehicles to collide may be considered responsible.

The CrashLink database contains a field for each vehicle specifying whether that vehicle was the key traffic unit in the accident it was involved in, i.e. whether it was the primary at-fault vehicle for that accident. We use this field to differentiate between vehicles that were at fault and those that were not. We then compare the proportion of at-fault vehicles or drivers to the proportion of not-at-fault vehicles or drivers to get a measure of the risk of accident involvement associated with a given risk factor or set of factors. We chose a set of seven risk factors to analyse in this way: driver age, driver gender, vehicle make, number of occupants of the vehicle, vehicle speed at time of crash, vehicle type and year of manufacture of the vehicle. Because induced exposure relies on determining the proportion of not-at-fault vehicles or drivers that possess a particular risk factor, it is not possible to use this methodology to analyse environmental risk factors. Thus our set of factors all relate to either vehicles or drivers.

Although the set of factors feasible for use here is limited by the available data, we are not so much concerned with the results obtained from this specific data set. The main goal is the ability to compute risk values for drivers and vehicles ahead of time.
CHAPTER 5. EXPERIMENTAL INVESTIGATIONS

Based on long-term characteristics, which can then be combined with more short-term risk factors and applied dynamically to inform behaviour. A thoroughly carried out study of risk factors is a separate and natural follow on activity from this thesis work.

5.1.2 Calculating Risk Values

To calculate the risk value for a given set of factors, we first need to calculate the proportion of the at-fault vehicles which have that factor using the key traffic unit field. For instance, in the crash database, 1604 of the key traffic unit drivers are listed as male, out of 2212 key traffic unit drivers total, giving us an at-fault population proportion of \( \frac{1604}{2212} = 0.725 \). Note that when calculating proportions, individual records are only included if all risk factors being considered are complete — if any fields are missing, those vehicles or drivers are excluded.

Following on, we estimate the proportion of not-at-fault vehicles or drivers having that risk factor. To continue the previous example, 1015 out of 1369 not-at-fault drivers were listed as male, giving us a proportion of \( \frac{1015}{1369} = 0.741 \) of the not-at-fault population. Finally, we take the ratio of the at-fault population proportion to the not-at-fault population proportion, giving us a risk value of \( \frac{0.725}{0.741} = 0.98 \). This method can be extended to any number of risk factors by selecting the proportions of the at-fault population and not-at-fault population that have all the risk factors in question.

5.2 Implementing the Risk Limit Model

The next section of work sought to evaluate the risk limit model as a whole, including all requisite steps in simulation experiments conducted using Paramics (see Section 3.5.1). This required first building a mechanism for simulating road accidents in Paramics. Next a simulation scenario was established and then used to determine the relationships between particular vehicle behaviours and the accident rate. The risk limit model was then able to be implemented in full and its effects on risk and utility measured. Further experiments were then conducted to investigate first risk-aware link choice and then social link choice.

Note that for this work I do not use the results from the previous section. While using a traffic accident database such as the NSW CrashLink database would be highly desirable for a real-world system, this initial implementation relies on simulations as
5.2. IMPLEMENTING THE RISK LIMIT MODEL

it is neither feasible nor ethical to implement a real-world system using the risk limit model until it has been thoroughly tested. The risk factors chosen in the previous section present significant difficulties in modelling and simulating them in Paramics. As such, I instead only use aspects of drivers and vehicles that are already modelled in Paramics, and use Paramics to determine appropriate risk values and vehicle behaviours.

5.2.1 Simulating Accidents

By default, Paramics does not have any mechanism for simulating traffic accidents. Hence, in order to study accident rate, it is first necessary to model accidents in the simulation. Although accidents are not themselves modelled in Paramics, the car-following model used extends to situations in which vehicles are separated by small distances — well below required stopping distances — and where acceleration and deceleration reach the physical constraints of the vehicle [128]. As such, it was possible to model traffic accidents in Paramics.

This is done by modelling dangerous behaviours that have the potential to lead to accidents. Vehicles in Paramics will by default never perform dangerous actions such as sudden braking, running a red light, changing lanes without checking for a gap etc. In reality however, most accidents are caused by such cases of human error [11, 13]. Two dangerous actions — sudden braking and lane changing without gap checking — have been implemented to act as potential causes of accidents. These actions are performed on a stochastic basis and braking can be of any magnitude up to the vehicle’s maximum deceleration.

The results of these actions are then left up to the simulation engine to play out, so that for many dangerous actions, no accident occurs as there are no other vehicles nearby or drivers are able to avoid colliding with the vehicle performing the dangerous action. Collisions are then detected using an oriented bounding box algorithm, which is appropriate in this case as vehicles in Paramics are modelled as rectangular prisms. Once vehicles have collided, they are removed from the simulation as we do not wish to model the effects of incidents but rather the frequency of accidents occurring, so it is important that all vehicles travel under the same conditions, i.e. without any incident-related congestion or road closures.
5.2.2 Road Network and Simulation Parameters

The road network used for the following experiments was a test network developed for this purpose. It consists of two links (forming one bi-directional road), each with four lanes, and two zones. Each zone acts as an origin for one of the links and a destination for the other. Vehicles are evenly distributed between the two links. Each simulation runs for two hours (simulation time) including warm-up. During this time vehicles are constantly released onto each link as fast as possible, i.e. vehicles will not exceed their maximum speed and will maintain headway according to the Paramics car-following model from the time they are released onto the link. A diagram of the road network can be seen in Figure 5.1. Each simulation was run 10 times for each datapoint, with the exception of the reference simulation, which had 100 runs.

5.2.3 Vehicle Behaviour and Accident Rate

In order to change the accident rate by modifying vehicle behaviour, it is necessary to first understand how particular behaviours affect the accident rate. To do this, we conducted experiments in which first maximum speed and then target headway were varied and the accident rate observed. These experiments were carried out using the test network described in Section 5.2.2 with a simulation duration of 2 hours for each run.

Each vehicle in Paramics attempts to drive at a maximum speed for the link it is currently on. Most of the time, the maximum speed matches the speed limit for the link, however under some circumstances this may be different for particular vehicle types or links, e.g. a heavy vehicle which has its speed limit set lower than that of the link it is on, or for vehicles with a high driver aggressiveness factor, which may seek to exceed the speed limit. However, using the programming API, it is possible
to manually set the maximum speed for each vehicle. This effectively represents the target speed for that vehicle, i.e. the speed it will travel at when not constrained by other, slower vehicles. Much of the time, vehicles will not travel at their maximum speed as they use the Paramics car-following model detailed in [128].

Target headway is the time a vehicle aims to keep between itself and a preceding vehicle, as opposed to headway which is the actual instantaneous time between the two vehicles. A vehicle will accelerate to get closer to the vehicle ahead if its current headway is greater than the target headway, and decelerate to get further away from the lead vehicle if its current headway is less than the target headway. The acceleration or deceleration applied also depends on the relative speeds of the two vehicles. Paramics breaks the headway–velocity-difference space into five regions, each of which have different behaviours. Further details on this can be found in the Paramics Technical Report [128].

5.2.4 Modifying Vehicle Behaviour

Having established a means of simulating and detecting accidents and gained an understanding of the relationship between particular vehicle behaviours and the accident rate, we were then ready to implement the risk limit model fully and use it to modify vehicle behaviour in response to changing risk conditions.

5.2.4.1 Determining Risk

The first step in adjusting vehicle behaviour to compensate for risk levels and maximise utility is to determine the risk value for each vehicle. However, this presents significant difficulties, especially in modelling risk factors, as discussed in Section 3.1, and so only the vehicle type was included in our initial experiments, with the added benefit that it was already modelled in some detail in Paramics. Differences between vehicle types include mass, height and width, and maximum deceleration. There were five different vehicles types in the simulation: car, large goods vehicle (LGV), other goods vehicle (OGV) types 1 and 2 (with differing dimensions), and coach.

To calculate the risk value for each type, we ran a reference simulation in which vehicle behaviour was not modified except for introducing dangerous actions as described in Section 5.2.1. The reference simulation consisted of 100 runs, each of which were
2 hrs (simulation time) in length, on the network described in Section 5.2.2. From this simulation, the accident rate for all vehicles was calculated by the formula

\[ R = \frac{N_c}{N_t} \]  \hspace{1cm} (5.1)

where \( R \) is the accident rate for all vehicles, \( N_c \) is the number of vehicles in collisions, and \( N_t \) is the total number of vehicles in the simulation. Note that the number of collisions is determined by the simulator playing out the results of introducing dangerous actions as per Section 5.2.1.

Accident rates were then calculated similarly for each vehicle type, giving a proportion of the vehicles of that type that were involved in collisions. The risk for a given vehicle type is given by

\[ r_T = \frac{R_T}{R} \]  \hspace{1cm} (5.2)

where \( r_T \) is the risk for vehicles of type \( T \), \( R_T \) is the accident rate for vehicles of type \( T \) and \( R \) is again the accident rate for all vehicles.

Risk values for each vehicle type obtained from the reference simulation are given in Table 5.1.

### 5.2.4.2 Adjusting Behaviour

Vehicle behaviour was adjusted according to a given risk limit. Vehicles with a risk value higher than the risk limit were required to adjust their behaviour so that they were driven more safely, thereby bringing them down to the limit. Vehicles with a risk value lower than the limit were allowed to be driven at higher risk, e.g. faster, in order to improve utility, i.e. average vehicle speed and overall throughput of the network.

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>Risk Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>0.999</td>
</tr>
<tr>
<td>LGV</td>
<td>2.710</td>
</tr>
<tr>
<td>OGV1</td>
<td>3.334</td>
</tr>
<tr>
<td>OGV2</td>
<td>1.568</td>
</tr>
<tr>
<td>Coach</td>
<td>3.345</td>
</tr>
</tbody>
</table>

Table 5.1: Risk values by vehicle type
5.2. IMPLEMENTING THE RISK LIMIT MODEL

Figure 5.2: The road network used for risk-aware link choice experiments. Vehicles travel along the feeder link to the first junction, where they must choose either the left or right link, depending on the vehicle’s risk value and current traffic conditions.

Three different vehicle behaviours were modified in this way: maximum speed, target headway and lane changing. The exact functions for modifying speed and headway are discussed in Section 6.2. Lane changing was modified in the following way. If the vehicle’s risk value was below the limit, the vehicle would attempt to change into the adjacent lane that would allow it to travel the fastest. If the vehicle’s risk value was above the limit, it would change into the lane which was the least risky — i.e. the lane in which surrounding vehicles had the lowest risk values, or a lane with no nearby vehicles if there was one. In cases where a choice was not clear, vehicles would choose the lane closest to the kerb.

5.2.4.3 Risk-Aware Link Choice

We again used Paramics to conduct an evaluation of the risk-aware link choice algorithm. The road network used consisted of a single feeder link to an intersection, at which there were two subsequent links, equal in length, which vehicles could choose. These two links then joined again into a single link to facilitate easier measurement of total throughput. The feeder and final links each had four lanes, while the intermediate links had two. All links were unidirectional. A diagram of the road network is shown in Figure 5.2.

The vehicles were given a lognormal distribution of risk values (mean = 1.0, standard deviation = 0.5) as this distribution best fits our definition of risk, i.e. that it is non-negative with a mean of 1.0. We also experimented with using a uniform and a normal distribution, and with varying the distribution parameters, however, the results were not qualitatively different.
In our experiments, the risk value of the right-hand link was held constant at 1.0, while the risk value of the left link was used as the independent variable. Since we calculate risk relatively and the values are used to compare links, it is only the difference in risk values between the links that is relevant. For each risk value, ten simulation runs of two hours duration (simulation time) each were performed.

We are primarily interested in determining whether vehicles are able to make dynamic risk-aware link choices and how this relates to congestion in the road network. As such, we do not consider the specific messaging protocol in the wireless network for relaying speed information between vehicles and assume only that it is possible for vehicles to obtain this information.

The risk limit used for these experiments was 1.1 and the maximum speed a vehicle could travel on a link was determined using the function given in Section 6.2.

### 5.2.4.4 Social Link Choice

The simulation environment used for the experiments on social link choice was similar to that described in Section 5.2.4.3, except that the number of lanes in the links was reduced. The feeder and final links were reduced to two lanes each and the intermediate links were reduced to one lane each so that the effect of each vehicle’s link choice on the following vehicles would be more apparent.

The social penalty multiplier was varied from zero (completely selfish) up to a value of 100. Additionally, the case where vehicles were completely selfless was tested. In this case, vehicles could only choose the link which gave them the best speed if there were no differences in the social penalty at all. Again, ten simulation runs of two hours duration each were performed for each data point. Three risk values — 1.5, 2.0 and 3.0 — were used for the left link in these experiments to give an idea of how the system’s behaviour varies with the ratio of risk values between the links.
Chapter 6

Results

Here I present the results of the experiments described in the previous chapter. I will first discuss the results of the analysis of the data from the NSW CrashLink database and its use in calculating risk values. Next I will cover the experiments concerning the effects of vehicle behaviours on accident rate within the Paramics simulator and derive functions for these. These were then applied to test the risk limit model as a whole and here I present results describing its effects on utility and accident risk. Lastly I present the results of the evaluations of the risk-aware link choice and social link choice algorithms.

6.1 Calculating Risk Values

Figures 6.1–6.9 give risk value calculations for each risk factor. For two factors, gender and number of occupants of the vehicle, we have also conducted the same analysis restricted to young drivers only. These factors have often been raised in the debate about licensing rules for young drivers and thus analysis specific to young drivers on these factors may prove of interest.

These results are generally consistent with the existing literature on accident rates and are thus not particularly surprising. However, they demonstrate how this methodology can be applied to produce individualised risk values for each driver and vehicle on the road from existing traffic accident data. This mainly applies to static or slowly-changing risk factors, such as those presented here, however this is a significant part of the risk attributable to any given driver or vehicle. More dynamic factors require a
CHAPTER 6. RESULTS

Figure 6.1: Risk values by gender

Figure 6.2: Risk values by gender for young drivers (age less than 25 years)
6.1. **Calculating Risk Values**

**Figure 6.3: Risk values by age**

**Figure 6.4: Risk values by vehicle make**
CHAPTER 6. RESULTS

Figure 6.5: Risk values by vehicle type

Figure 6.6: Risk values by number of occupants of the vehicle
6.1. **CALCULATING RISK VALUES**

Figure 6.7: Risk values by number of occupants of the vehicle for young drivers (age less than 25 years)

Figure 6.8: Risk values by vehicle speed at time of crash
differently approach in order to be incorporated into the risk model.

Calculations of this sort may take significant time relative to the necessary response time of a traffic management application, particularly for combinations of many factors. However, these calculations would not need to be performed every time a risk value was needed, as results could be pre-computed and stored for fast look-up. This means that providing individual, differentiated risk estimates, a requirement of our risk limit traffic management model, is viable.

Additionally, as VANETs see more widespread use, we can expect more and better quality data to become available for calculating risk values. In particular, VANETs promise an unprecedented opportunity to gather complete and accurate exposure data for traffic accident risk, as vehicles will be constantly transmitting their state and characteristics over the network. Collection and management of this data brings its own set of challenges, in particular with regards to the sheer scale of data to be collected and management of road users’ privacy. Nonetheless, risk estimates should become more accurate and incorporate more risk factors in the future. This is examined further in Chapter 10.
6.2 Vehicle Behaviours

I now present results of the experiments to determine the relationship between vehicle behaviours and accident rate in Paramics, described in Section 5.2.3. In the first experiment, the maximum speed was varied by a factor ranging from 0.1 in the first set of simulations to 3.5 in the last set. This was multiplied by the default maximum speed for that vehicle. The accident rate was then observed (see Figure 6.10). A line of best fit was calculated to give an approximation of the relationship between speed and accident rate in Paramics and is given by

\[
f(x) = 0.004x - 0.0015. \tag{6.1}
\]

Since here we are varying maximum speed — i.e. a vehicle’s target speed — not the actual speed vehicles travel at, the speed vehicles will travel at is affected not only by this parameter but also constraints due to other traffic. This results in a relatively complex, non-linear relationship with accident rate and finding a good fit for this function was non-trivial. However, for our purposes, it is not necessary to fully investigate this function but we instead choose to take a simple linear approximation as an initial estimate. As will be seen in Section 6.3, this is sufficient to achieve improvements in road system efficiency whilst maintaining the accident rate.

The second experiment involved varying the headway factor of the vehicles. The default headway in Paramics is 1 s, however, each vehicle also has a headway factor, primarily based on the vehicle type, which is multiplied by the default headway in order to give a target headway for that vehicle. To test the effect of target headway on accident rate, an additional headway factor, ranging from 0.1 in the first set of simulations to 3.5 in the last set, was multiplied by the target headway of each vehicle. The resulting accident rate function is shown in Figure 6.11. A decaying exponential function was fitted to this curve, with the resulting function of

\[
f(x) = 0.007e^{-x/1.44} + 0.0002. \tag{6.2}
\]

The exact functions for modifying speed and headway are derived from these curves of best fit. The function for maximum speed is

\[
s = k + \frac{0.0037 + 0.0015r}{0.0041r} \tag{6.3}
\]
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Figure 6.10: Effect of maximum speed on accident rate

Figure 6.11: Effect of headway factor on accident rate
where $s$ is the maximum speed factor, which is multiplied by the default maximum speed given by the Paramics simulation engine, $k$ is an adjustment constant of -0.2, so that maximum speed is slightly under-estimated, and $r$ is given by

$$r = \frac{\text{risk(vehicle)}}{\tau} \quad (6.4)$$

where $\tau$ is the risk limit.

The headway function is

$$h = k - 1.437 \ln \left( \left( \frac{0.0037}{r} - 0.000158 \right) \times \frac{1}{0.0065} \right) \quad (6.5)$$

where $h$ is headway factor, which is multiplied by the vehicle’s default headway factor given by the Paramics simulation engine, $k$ is an adjustment constant of 0.2, so that headway factors are slightly over-estimated, giving an overall decrease in risk at the cost of some utility, and $r$ is given by

$$r = \frac{\text{risk(lead vehicle)} \times \text{risk(following vehicle)}}{\tau} \quad (6.6)$$

where $\tau$ is the risk limit.

We include the adjustment constants $k$ in these functions to ensure the desired risk limit is met. The functions presented here to relate vehicle behaviours to accident rates are not exact and as such there is inherent error in using them to compensate for risk. We thus choose to take a slightly conservative value when applying these functions. As the accuracy of the risk limit model improves over time, it is possible the $k$ values may decrease or be dispensed with altogether.

### 6.3 Evaluating the Risk Limit Model

I now present results from the evaluation of the risk limit model as a whole, described in Section 5.2.4.2. Simulations were run with risk limits ranging from 0.1 to 3.5, with 10 simulation runs for each value. The results are shown in Figures 6.12, 6.13 and 6.14, plotted with 95% confidence intervals.

Table 6.1 gives the values of accident rate, average vehicle speed and arrival rate (number of vehicles arriving at their destination per unit time) for risk limits between 0.7 and 1.5, as well as percentage differences from the reference simulation. Instances
CHAPTER 6. RESULTS

Figure 6.12: Accident rate vs. risk limit

Figure 6.13: Average vehicle speed vs. risk limit
where the results were improved over the reference simulation are in bold.

We can see that for risk limits between 1.1 and 1.4 inclusive, we get an improvement in all three measures. Accident rates in this region range from 91.52% to 92.64% of the reference rate, while average speed is improved by between 21.98% and 74.61% of the reference. The arrival rate shows improvements from 5.83% to 15.61%. For risk limits outside of this region, one or more of the measures is improved, however this comes at a price — we may have decreased accident risk but average vehicle speed and arrival rate are also below the reference level, or the utility (throughput and speed) of the network may be improved, but the accident rate is also increased above the reference.

6.4 Risk-Aware Link Choice

We now examine the results of the experiments on risk-aware link choice described in Section 4.4.1. Figure 6.15 shows the number of vehicles choosing each link as well as the total vehicle count (i.e. throughput) as the risk value of the left link varies. Because the key determiner of link choice is the risk difference between the two links, varying the right link’s risk would be an exactly symmetrical case and thus we omit it. As would
Table 6.1: Detailed results of the risk limit model evaluation. Bold text indicates improvements over the reference simulation.

<table>
<thead>
<tr>
<th>Arrival Rate (vehicles/s)</th>
<th>Average Vehicle Speed (m/s)</th>
<th>Average Vehicle Speed (mi/h)</th>
<th>Arrival Rate %</th>
<th>Arrival Rate %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>0.0037</td>
<td>100.00</td>
<td>10.54</td>
<td>100.00</td>
</tr>
<tr>
<td>0.7</td>
<td>0.0031</td>
<td>85.54</td>
<td>0.81</td>
<td>100.00</td>
</tr>
<tr>
<td>0.8</td>
<td>0.0032</td>
<td>90.02</td>
<td>0.63</td>
<td>100.00</td>
</tr>
<tr>
<td>0.9</td>
<td>0.0031</td>
<td>85.54</td>
<td>0.72</td>
<td>100.00</td>
</tr>
<tr>
<td>1.0</td>
<td>0.0034</td>
<td>91.52</td>
<td>0.80</td>
<td>100.00</td>
</tr>
<tr>
<td>1.1</td>
<td>0.0034</td>
<td>91.52</td>
<td>0.86</td>
<td>100.00</td>
</tr>
<tr>
<td>1.2</td>
<td>0.0035</td>
<td>94.13</td>
<td>0.90</td>
<td>100.00</td>
</tr>
<tr>
<td>1.3</td>
<td>0.0034</td>
<td>94.13</td>
<td>0.93</td>
<td>100.00</td>
</tr>
<tr>
<td>1.4</td>
<td>0.0035</td>
<td>94.13</td>
<td>0.94</td>
<td>100.00</td>
</tr>
<tr>
<td>1.5</td>
<td>0.0042</td>
<td>114.68</td>
<td>1.1</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Figure 6.15: Vehicle link choice when using the risk-aware link choice algorithm.

be expected, more vehicles chose the link with the lower risk as it allows for travel at higher speeds. However, despite the lower risk link being a priori a better choice, some vehicles did choose the higher risk link due to congestion on the lower risk link.

Figure 6.16 shows the average risk of vehicles choosing each link. The average risk was lower for vehicles choosing the high risk link, indicating that low risk vehicles could more readily change their preference to the high risk link in order to get a speed increase under congestion conditions. Here, vehicles do not have a direct measure of congestion but rather make their link choices based on the link speed, as discussed in Section 5.2.4.3. For higher risk vehicles, congestion would not cause as significant a slowdown (or none), since their higher risk limits them to a lower speed in the first place.

## 6.5 Social Link Choice

Lastly, we have the results of the social link choice experiments discussed in Section 5.2.4.4. Figures 6.17 and 6.18 show how the arrival rate (i.e. throughput) and average vehicle speed vary with the social penalty multiplier (defined in equation 4.2), with 95% confidence intervals. In these figures, the infinity symbol represents the case where
vehicles were completely selfless and could only choose the link which gave them the best speed if the social penalties were exactly equal across the two links. From these figures, we can see that neither completely selfish nor completely selfless behaviour produces the best results in terms of overall utility of the road system, but rather an intermediate strategy works best.

Figures 6.19 and 6.20 show the minimum and maximum values for the average speed of any vehicle in each simulation. As can be seen in the figures, the range of speeds remained consistent throughout. However Figure 6.21, which shows the standard deviation of individual vehicles’ average speeds, shows that the speed varied least when vehicles were entirely selfish, i.e. a selfish strategy provides for greater consistency between vehicles in terms of their speeds. Figure 6.22 provides a larger plot of the speed standard deviation data points for social penalty multipliers from 0 to 10. The speed standard deviation was highest when the average vehicle speed was also highest, indicating that there is a trade-off between obtaining the best speed and fairness to all vehicles over a single link. It is not clear without further work whether this result would persist in a larger network with more link choices, since it is possible that averaging may occur over several links, with a vehicle which is disadvantaged on one link instead preferred on others, which would lead to greater fairness in the system.
6.5. SOCIAL LINK CHOICE

Figure 6.17: Vehicle arrival rate vs. social penalty.

Figure 6.18: Average vehicle speed vs. social penalty.
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Figure 6.19: Maximum average vehicle speed vs. social penalty

Figure 6.20: Minimum average vehicle speed vs. social penalty
6.5. **SOCIAL LINK CHOICE**

Figure 6.21: Standard deviation of average vehicle speed vs. social penalty

Figure 6.22: Standard deviation of average vehicle speed vs. social penalty
These results were consistent across the different risk values for the left link that we tested, showing that these trends do not rely on a particular set of relative risk values for the links.

From these results, along with those shown in Section 6.4, we can see that it is feasible to use this method to implement vehicle link choice that takes accident risk into account. This algorithm provides emergent load-balancing between the links as vehicles adapt to changing congestion conditions. Additionally, with the inclusion of the social penalty, vehicles can also consider the utility of following vehicles, along with risk, when making link choices. The social link choice algorithm provides a means to balance individual utility of a given vehicle against the collective utility of all vehicles together.