On Road Network Utility Based on Risk-Aware Link Choice

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On Road Network Utility Based on Risk-Aware Link Choice

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***Abstract*— We have previously shown how it is possible to lower accident risk levels while at the same time increasing traffic flows with the aid of vehicular ad-hoc networks. In this paper, we extend the online traffic accident risk mitigation system to include link choice. We develop an algorithm that allows vehicles to choose road links that provide the current maximal utility, based on information received over a vehicular network, whilst remaining below acceptable risk levels. Additionally, we investigate how to improve the performance of this algorithm by considering the effect a vehicle's link choice has on the utility of other vehicles. We introduce a social penalty for reducing other vehicles' utility and investigate the effects of including this as a factor in vehicles' link choices. The resulting system sheds new light on the problem of effective link choice by route selection algorithms and highlights the potential that exists in VANET-based traffic management.**

I. Introduction

Route choice, that is, the path a vehicle chooses in the road network in order to reach its destination, has a significant bearing on accident risk, through factors such as road type, intersections, geometry and other features all contribute to accident risk [1], [2]. When taking route decisions, drivers have been shown to adjust their choices in response to perceived accident risk [3], [4]. As we move increasingly towards ITS-based approaches to route choice — from satellite navigation systems providing routing advice to drivers up to self-driving vehicles where the route is chosen entirely autonomously — accident risk should be a consideration in addition to travel time or other measures of utility. By utilising a vehicular network, risk information can be dynamically updated and always kept relevant to the current situation, allowing vehicles to include up-to-date risk information about the links ahead in their routing decisions.

In [5], [6], we proposed a system for traffic accident risk mitigation based on differentiated vehicle behaviour (Fig. 1). Each vehicle calculates and updates its risk level as it receives new information over the network, and compares it to a given threshold: the risk limit. We model risk as a relative measure, with a reference value of 1.0 representing an average risk level across all vehicles, drivers and situations. Any risk factors included then increase or decrease the risk level relative to this; for instance, a risk value of 2.0 represents a doubling in the probability of an accident occurring. Road users must aim to keep their risk levels under the risk limit and to this end, when a vehicle's current risk exceeds the threshold, either the driver or the vehicle itself takes risk-mitigating behaviours such as reducing speed, increasing headway, or changing into a lane with a lower risk value. However, when a vehicle's current risk is below the threshold, it may engage in utility increasing behaviours, where utility is considered in terms of vehicle speed and road network flow. Our system does not dictate how action takes place and is equally applicable to driver and autonomous vehicle controlled actuation.

In this paper, we extend this model to include link choice. 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 in order to maintain a sufficiently low risk level and the converse is true for a less risky link.

Previous work on vehicle routing choices has primarily focused on utility such as attempting to reduce vehicle travel time. There have been some examples of incorporating accident risk into vehicles' routing choices [7]–[9]. However, this work has either relied on static (or only slowly-changing) accident risk models, global knowledge across the road network, or both. In contrast, our work in this paper will focus on using our risk model which allows for highly dynamic and distributed calculation of accident risk [6]. This makes it suitable for implementation in a vehicular ad-hoc

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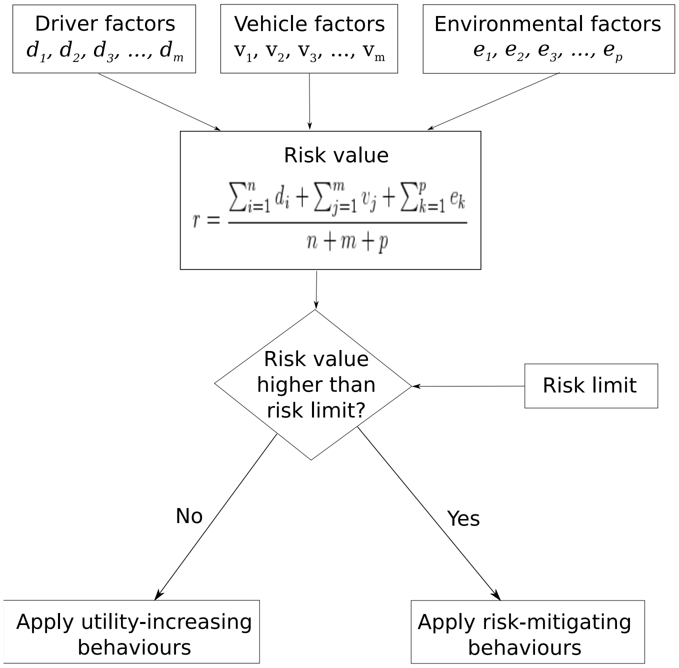

Fig. 1. A model for dynamic, online traffic accident risk mitigation

network and use by vehicles in real-time without relying on communications to a centralised controller.

In section II, we provide an algorithm for vehicles to make risk-aware link choices and present experimental results demonstrating its effectiveness. 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. Section IV discusses how this might be extended to include risk in end-to-end route choices.

Additionally, in section III, we investigate how to improve the performance of this algorithm by considering the effect a vehicle's link choice has on the utility — as measured by throughput and vehicle speed - 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 include a social penalty for reducing utility of other vehicles and investigate the effects of including this penalty as a factor in vehicles' link choices.

Finally, section IV discusses some of the questions raised by this work and directions for future investigation.

II. Risk-Aware Link Choice

To include accident risk in vehicle link choices, we first need to assign a risk value to each link. This can be calculated in a way similar to vehicle risk calculations in [5], 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 intersections. However, since we are 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 assign each link a value as outlined in section II-A.

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, take the average of the vehicle risk and the link risk.

$$r = \frac{r_v + r_l}{2} \tag{1}$$

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 using both vehicle risk and link risk as independent variables and thus varying them 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.

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). A brief description of how this maximum speed is determined can be found in section II-A; for full details, we refer the reader to [5].

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

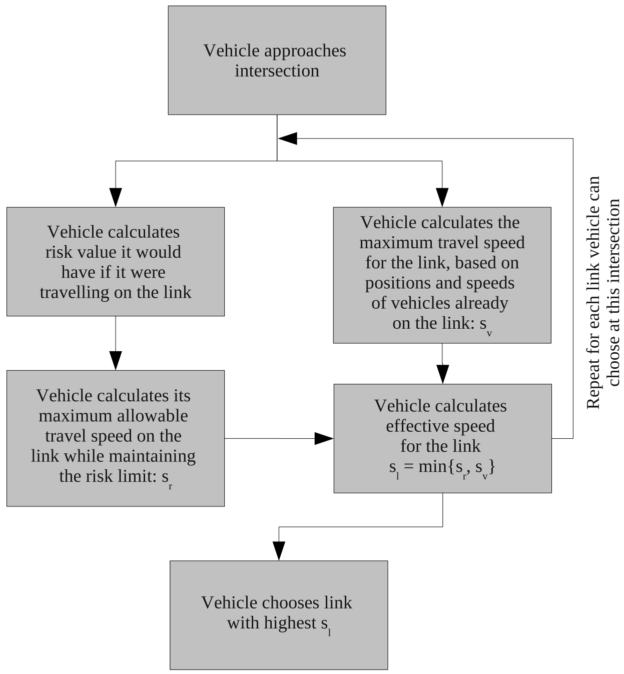

Fig. 2. Road network used for risk-aware link choice experiments

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 then chooses the link with the highest effective speed as its next link.

The risk-aware link choice algorithm is summarised in Figure 2.

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 slow (high risk) vehicle is already travelling 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.

A. *Experimental Set-up*

We used the Quadstone Paramics microsimulator [10] to conduct an evaluation of the risk-aware link choice algorithm. This simulator models vehicle behaviour in detail, including models for car following, lane changing, gap acceptance and other driver behaviour. For more details on these models, see [11] and [12]. The road network used consisted of a single feeder link to an intersection, at which there were two subsequent links, equal in length,

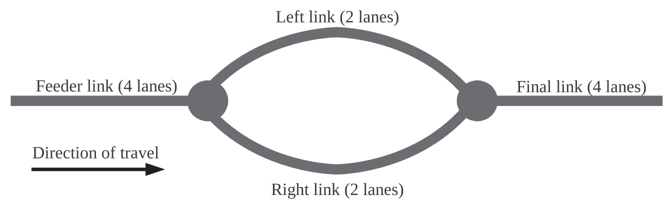

Fig. 3. Road network used for risk-aware link choice experiments

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 Fig. 3.

We assigned the vehicles a lognormal distribution of risk values (mean: 1.0, stddev: 0.5) as this distribution 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.

To determine the maximum speed a vehicle can travel on a link, we take the default maximum speed as calculated by the simulator, and apply a multiplier α given by

$$\alpha = 0.17 + \frac{0.90r}{r_L} \tag{2}$$

where r is the total risk as determined by (1) and r_L is the risk limit. This function has been derived empirically for the simulation environment we use (see [5] for details) and its coefficients would likely need to be recalibrated for use elsewhere.

For these experiments, we assume all vehicles are equipped with our risk-aware link choice and accident risk estimation systems and are thus homogeneous in their link choice method (but not in their actual risk values). 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. For an examination of risk information exchange in our model and how it is affected by network phenomena, see [6].

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. All figures below are shown with 95% confidence intervals. The risk limit used for these experiments was 1.1.

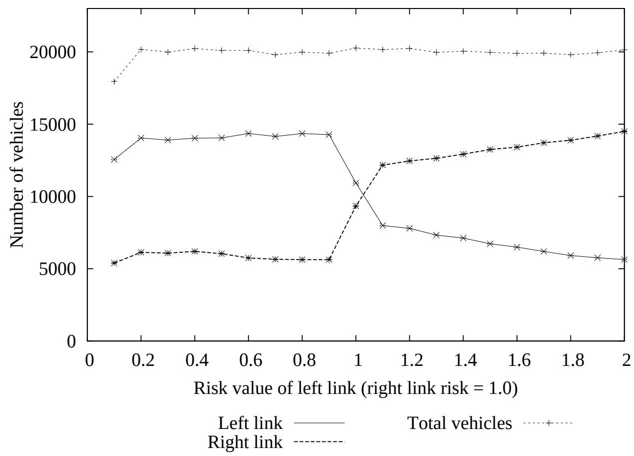

Fig. 4. Vehicle link choice. Confidence intervals for this figure are too small to be shown clearly.

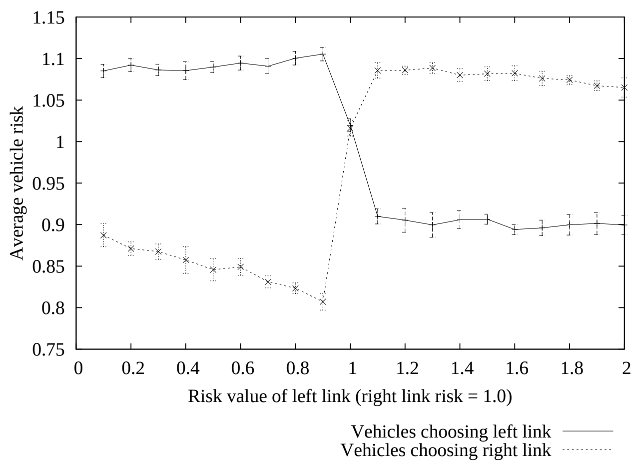

Fig. 5. Vehicle risk by link choice

B. Results

Fig. 4 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. As would 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.

Fig. 5 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. 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.

III. Social Link Choice

In the previous section, vehicles always chose the link that gave them the highest speed. Now we present a link choice algorithm where vehicles also consider the effects their choices have on other vehicles.

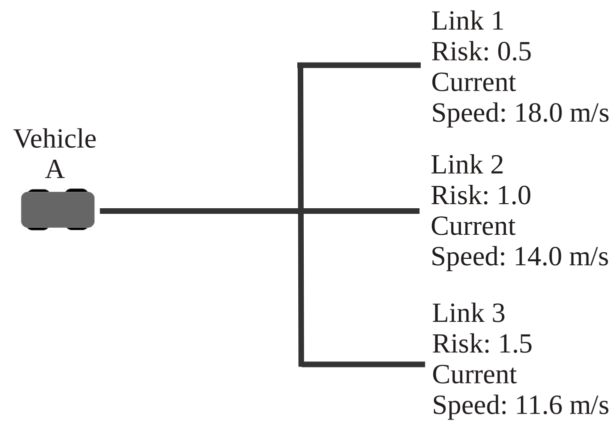

Fig. 6. Vehicle A's preferred link is link 1, however the maximum speed vehicle A can travel on this link is only 16.09m/s, which is lower than the current link speed of 18.0m/s

TABLE I
Maximum speed vehicle A can travel on each link

Link	Link risk	Link maximum speed (m/s)
1	0.5	16.09
2	1.0	13.33
3	1.5	11.45

A. 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. Fig. 6 gives an example of such a scenario.

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

The current link maximum speeds for the links are 18.0m/s for link 1, 14.0m/s for link 2 and 11.6m/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 16.09m/s, a reduction of 1.91m/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 II 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 for vehicle speeds and risk chosen for this example are not unusual and as such the situation described above, in which one link would give the best speed for a vehicle,

TABLE II

REDUCTION IN LINK SPEED CAUSED BY VEHICLE A CHOOSING EACH LINK

Link	Current link maximum speed (m/s)	Vehicle maximum speed for vehicle A (m/s)	Speed reduction if vehicle A chooses this link (m/s)
1	18.0	16.09	1.91
2	14.0	13.33	0.67
3	11.6	11.50	0.10

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 and speed reduction for other vehicles.

B. 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: the current link maximum speed minus the vehicle maximum speed. The social penalty is always non-negative — if the speed difference is negative, the social penalty is set to zero — as the vehicle is still constrained by the speed of the vehicles in front of it.

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

$$c = s - p \times M \tag{3}$$

where c is the score for the link, s 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 the following section, we describe experiments carried out to test the effect of incorporating social penalties into vehicle link choices.

C. Experimental Set-up

The simulation environment used for these experiments was similar to that described in section II-A, 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 in order to make the social effects of vehicles' link choices more apparent.

The social penalty multiplier was varied from zero (completely selfish) to 100. Additionally, the case where vehicles

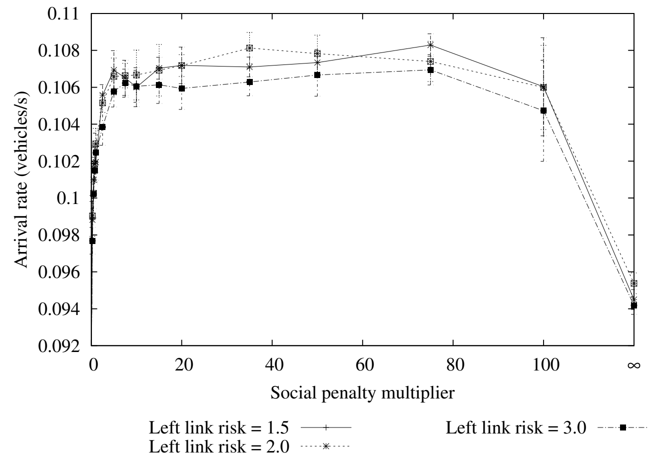

Fig. 7. Arrival Rate

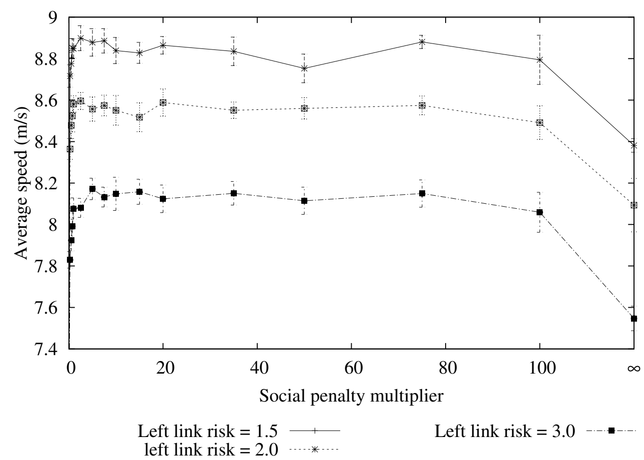

Fig. 8. Average vehicle speed

were completely selfless was tested, denoted by the infinity symbol in the figures in the following section. In this case, vehicles could only choose the link which gave them the best effective 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, and figures are shown with 95% confidence intervals. Three risk values for the left link were used for these experiments: 1.5, 2.0 and 3.0.

D. Results

Fig. 7 and 8 show how the arrival rate (i.e. throughput) and average vehicle speed vary with the social penalty multiplier. From these figures, we can see that neither completely selfish nor completely selfless behaviour produces the best results in terms of overall utility — throughput and average vehicle speed — of the road system, but rather an intermediate strategy works best.

Fig. 9 and 10 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, Fig. 11, which shows the standard deviation of individual vehicles' average speeds,

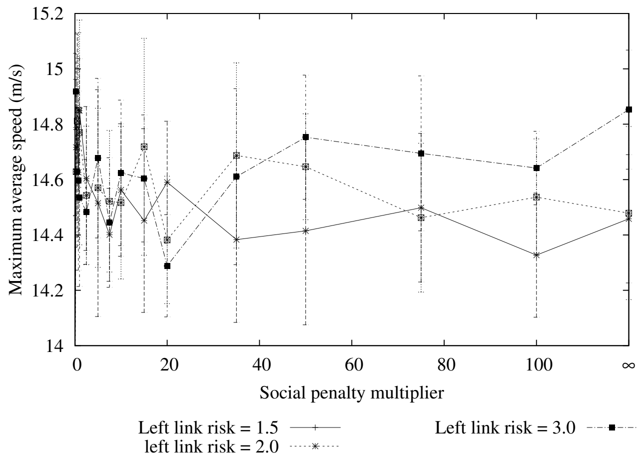

Fig. 9. Maximum average vehicle speed

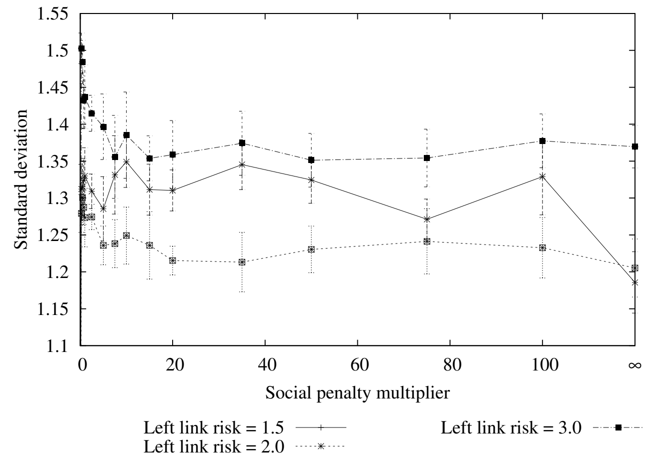

Fig. 11. Standard deviation of average vehicle speeds

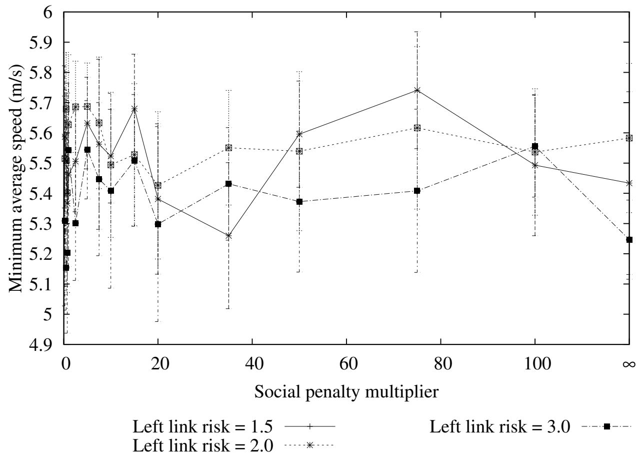

Fig. 10. Minimum average vehicle speed

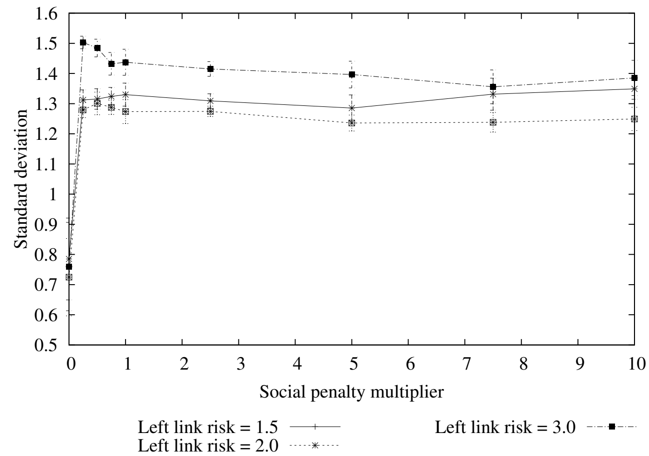

Fig. 12. Standard deviation of average vehicle speeds

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. Fig. 12 provides a larger plot of the speed standard deviation data points for social penalties 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 preferenced on others, which would lead to greater fairness in the system.

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.

IV. Future Work

Thus far, we have considered the choice of only a single link. However, vehicles are unlikely to face such choices in isolation — the situation where a vehicle must decide amongst links that are equally useful in getting to its destination does not occur very often. Instead, a link choice will typically be part of an entire route. We now consider two approaches to extending this work to deal with end-to-end route choice.

The first approach would be to use a similar process as in section II but consider entire routes rather than single links. This would require calculating trip time over the entire route, taking into account the risk levels of each link along the route as well as current traffic conditions, and optionally incorporating social penalties as in section III. This then becomes a shortest-path problem, where the edge weights are determined by not only travel time, but also risk and social cost.

However, using such a system, travel speeds along any given link are far more variable than in existing systems, as each vehicle adjusts its speed in accordance with its current risk level, although the use of social penalties mitigates this somewhat. A vehicle's risk level also depends on the vehicles around it, and so traffic conditions on the link influence travel speed not only by slowing them when there is congestion, but also by varying the current risk level and thus the maximum speeds vehicles can travel at. In addition, we have the usual variance in travel time due to traffic density changing with the time of day and other factors.

While the shortest-path problem is well-studied, standard algorithms such as Dijkstra's [13], may produce suboptimal solutions in the case of dynamic and stochastic systems [14]. There is substantial previous work in this area, with a range of approaches that have been developed to deal with the time-varying and uncertain nature of traffic routing and travel time prediction [8], [14]–[17]. Further work is required to determine the best approach under the conditions described above.

The second approach would be to include a measure of how useful each possible link at a given intersection is in reaching the destination and use this in calculating the score for that link, with links that cannot be used to reach the destination having a score of zero. This approach is more similar to the single link choice problem we have investigated and would be easier to adapt dynamically to changing conditions, however it could also result in the overall route being less optimal than an end-to-end approach.

V. Conclusion

We have extended our risk model developed in [5] and [6] to include vehicle link choice. This is an important vehicle behaviour as road links are significant sources of risk and so the ability to mitigate this is crucial in a system for traffic accident risk management. We have developed an algorithm for risk-aware link choice which deals gracefully with congestion, varied risk difference between links and any number of links to choose from.

We investigated strategies for incorporating the effect a vehicle's link choice has on following vehicles by including a social penalty as a factor in link choice. These strategies ranged from completely selfish to completely selfless. We found that an intermediate strategy is the best approach for maximising road system utility. However, including a social penalty causes greater variance in average speeds from vehicle to vehicle and so fairness is a concern that needs further attention. Since the experiments were carried out over a single link it is necessary to extend the experiments to incorporate multiple link networks. It is not unlikely that several consecutive links will result in statistical averaging of the variance, hence increased fairness for the vehicles.

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