Routing Traffic for Community Health:
The Case with Safety-Conscious Travelers

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by
Rui Ma, Michael Zhang[1]

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[1] Project Principal Investigator.

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16. Abstract

Safety awareness among travelers has become one of the influential factors on travelers' choice behaviors. Yet most existing studies on vehicular routing or traffic assignment problems largely assume that travelers' route choice is only based on travel time instead of considering safety awareness. This report summarizes the effort of implementing the safety awareness indexes into consideration for link-node-based travelers' route choices. Such safety awareness indexes are associated with the average accident risk on each road segment on the travelers' routes, which was dependent on traffic volumes and road types. Through numerical studies on three different networks, it is found that the resulting traffic flow pattern from safety awareness based route choices, either in term of user equilibrium or system optimum, are significant different from their counterparts based on travel time.

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Routing Traffic for Community Health: The Case with Safety-Conscious Travelers

Rui Ma, Michael Zhang*

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Abstract

Safety awareness among travelers has became one of the influential factors on travelers' choice behaviors. Yet most existing studies on vehicular routing or traffic assignment problems largely assume that travelers' route choice is only based on travel time instead of considering safety awareness. This report summarizes the effort of implementing the safety awareness indexes into consideration for link-node-based travelers' route choices. Such safety awareness indexes are associated with the average accident risk on each road segment on the travelers' routes, which was dependent on traffic volumes and road types. Through numerical studies on three different networks, it is found that the resulting traffic flow pattern from safety awareness based route choices, either in term of user equilibrium or system optimum, are significant different from their counterparts based on travel time.

1 Introduction

Traffic safety plays a critical role in community health. Reported by National Highway Traffic Safety Administration (Blincoe et al., 2015), there were 3.9 million injured in motor vehicle crashes in the year 2010 in the United States. According to Public Health Foundation (Public Health Foundation), motor vehicle crashes result in 2.7 million emergency department visits annually. There were 37,133 fatality in motor vehicle traffic crashes on U.S. roadways during 2017, which came after two yearly consecutive increases in 2015 and 2016 (National Highway Traffic Safety Administration and others, 2018). It was estimated that each fatality resulted in an average discounted lifetime cost of $1.4 million (Blincoe et al., 2015).

Travel safety is a major concern of not only the planning agencies, traffic operational managers and public health agencies but also common travelers. From different perspectives, studies reveal that nowadays younger travelers are especially more safety conscious. A survey conducted in 2017 (Carlson Wagonlit Travel, 2017) revealed that business travelers in the age group 24-34 (i.e., millennials) are more concerned about their own personal safety than other generations. A report on travel insurance research in 2018 (Berkshire Hathaway Travel Protection, 2018) indicated that younger travelers (ages 25 to 44) are very travel-safety conscious, as they have the greatest increase in travel insurance buying intent for the second year in a row, compared with other age groups.

The safety consciousness of travelers are also revealed by the technologies usage by travelers. Navigation applications on smartphones gain strong popularities because such apps are able to provide not only the real-time travel time updates for various route choices, but also information on travel safety. For instance, the popular navigation app Waze enables users to self-report and receive incident information on roads in a crowd-sourcing manner, such as hazardous material, accidents. etc. Similar information are distributed via other on-line map services such as Google Maps and Here-we-go.

Traditional vehicle routing and traffic assignment problems usually consider travel time or expected travel time, which indicates the road congestion level, as the sole indicator influencing travelers' route choices. The literature on such a topic is very rich in the recent decades, see some representative studies in Bellman (1958);

*Project Principal Investigator: Michael Zhang, hmzhang@ucdavis.edu

Fleischmann et al. (2004); Kim et al. (2005); Gueziec (2008); Ban et al. (2012); Gendreau et al. (2015); Chai et al. (2017). However, studies taking safety consciousness into consideration for the vehicle routing or traffic assignment problems are relatively very sparse. In Przybyla et al. (2011), crash occurs with probabilities; when crash occurs, it leads to flow capacity reduction, so that the routing with respect to crash is converted into the routing problem with respect to flow capacity reduction, which is similar to an increase of travel time with the use of BPR-type travel time functions. In Omidvar et al. (2017), a mixed-integer optimization problem was proposed to minimize the crash probability on all routes. The objective function is composed by the multiplication of crash probability of all selected links. However, such crash probability is static for given departure time and does not respond to the amount of traffic flow on the link.

In this report, we propose the vehicle routing traffic assignment models by using the average accident risks as the safety awareness indexes on each individual road segment (i.e., a link in the road network) for the travelers. Such link-based accident risks were developed by Kweon and Lim (2014) from the real world crash data in Virginia. Similar accident risk metrics were conducted in Economic Evaluation Manual in New Zealand (Kingsbury, 2016).

The rest of this report is organized as follows. Section 2 lists the notation used in the following sections. Section 3 reviews the accident risks on various types of roads and develop the safety awareness indexes for individual travelers on a road segment. Section 4 formulates a network equilibrium model in user equilibrium, where each traveler minimizes his or her own accident risk. Section 5 formulates a system optimal traffic assignment, which indicates the best performance benchmark that travelers cooperate to minimize the total accident risks in the network. Section 6 evaluates system performances for both scenarios with numerical examples. Section 7 concludes this report.

2 Notation

$\mathcal{N}$ Network node set $\{1, 2, \cdots, N\}$

$\mathcal{L}$ Network link set; $(i, j) \in \mathcal{L}$ is a directional link from node i to j

Parameters all positive scalars

L_{ij} Length of link (i, j)

τ^0_{ij} Free flow travel time on link (i, j)

C_{ij} Flow capacity of link (i, j)

R_{ij} Road type of link (i, j);

e.g., $R_{ij} = 1$ for Urban freeway segments - 4 lanes;

$R_{ij} = 2$ for Urban multilane divided arterial segments

D_{os} Origin-destination demand from node o to s, $o, s \in \mathcal{N}$

Variables

sa_{ij} Accident risk for individual travelers on link (i, j)

v^s_{ij} Flow rate on link (i, j) going to destination s

π^s_i Node potential (nodal minimal accident risk)

from node i to destination s at User Equilibrium with respect to accident risk

3 Brief review of link-based accident risks and the development of safety awareness indexes

This section briefly reviews the accident risks on various types of roads, which was investigated in Kweon and Lim (2014) as the safety performance functions (SPFs). Then the safety awareness indexes used in this study are developed for individual travelers on a road segment.

3.1 Safety performance functions

SPFs reflecting Virginia conditions were developed in Kweon and Lim (2014) for multilane highway and freeway segments. The SPFs were developed by regression analysis by using a specific functional form, where the expectation of total number of crashes on a road segment in a year is the multiplication of three terms - an exponential of parameter α, a power function of the annual average daily traffic volume (AADT) on related road segment(s), and the length of the road segment. The crash data were collected from the year of 2004 to 2008 on 20,235 multilane highway segments and 2,905 directional freeway segments in Virginia for the development of the statewide SPFs. Among these, there were 4 subtypes of multilane highway segments and 10 subtypes of freeway segments.

With respect to the road segment types, different functional terms are used. For freeway segments, the predicted crash frequency per year per direction for segment a is modeled in the following term -

$$F_a = e^{\alpha} \times \mathrm{AADT}^{\beta}_{a,\text{One direction}} \times L_a,$$

where α is the intercept coefficient, β is the slope coefficient, $\mathrm{AADT}_{a,\text{Onedirection}}$ is the one-directional AADT, L_a is the segment length.

For multilane highway segments, the predicted bi-directional crash frequency per year for segment a is modeled in the following term -

$$F_a = e^{\alpha} \times \mathrm{AADT}^{\beta}_{a,\text{Two directions}} \times L_{\text{centerline}},$$

where α is the intercept coefficient, β is the slope coefficient, $\mathrm{AADT}_{a,\text{Twodirection}}$ is the bi-directional AADT, $L_{\text{centerline}}$ is the segment length measured on the centerline of the bi-directional segment.

Note that the coefficients for different types of segments are not the same. In Kweon and Lim (2014), the coefficients for 4 subtypes of multilane highway segments and 10 subtypes of freeway segments were determined in Tables 2 and 3. Taken from all these subtypes of road segments, in this report we select two representative subtypes in urban areas for our studies, which are 'urban multilane divided arterial segments' (referred as 'multilane' in short thereafter) and 'urban freeway segments -4 lanes' (referred as 'freeway' in short thereafter). Further, we only focus on the predicted total crashes (Table 2 in Kweon and Lim (2014)) rather than fatal and injury crashes (Table 3 in Kweon and Lim (2014)). Without losing the generality, the analyzing methods in the following sections can be easily extended to other subtypes or different types of crashes by revising the corresponding coefficients.

For 'multilane', the predicted crash frequency is

$$F_a = e^{-9.14} \times \mathrm{AADT}^{1.07}_{a,\text{Two directions}} \times L_{\text{centerline}}.$$

For 'freeway', the predicted crash frequency is

$$F_a = e^{-18.05} \times \mathrm{AADT}^{1.98}_{a,\text{One direction}} \times L_a.$$

It is worthy pointing out that for 'multilane', the predicted crash frequency is dependent with the bi-directional traffic volume. Such dependency is hardly modeled for other traffic performance indicators such as travel time, congestion level or level-of-service, which all use traffic volumes in one direction as the independent variable. The dependency on the total traffic volumes in both directions for multilane segments will lead to interesting behavioral responses in the following user equilibrium and system optimum vehicle routing/traffic assignment models.

3.2 Travelers' safety awareness indexes on a link

SPFs reflect the predicted numbers of crashes for a road segment in a year, which are for all travelers on such a road segment in a year. For each individual traveler, their safety awareness is equivalent to the average predicted numbers of crashes on a road segment (i.e., a link in a link-node representation network) in a year. In short, the safety awareness for individual travelers on link a is

$$sa_a = F_a / \mathrm{AADT}_a.$$

Specifically, for 'multilane' and 'freeway', the meaning of AADT are different. For 'freeway', the AADT refers to one directional traffic, while for 'multilane', it refers to bi-directional traffic in total. Therefore, the safety awareness index for 'multilane' is explicitly derived as

$$sa_a = e^{-9.14} \times \mathrm{AADT}_{a,\text{Two directions}}^{0.07} \times L_{\text{centerline}}.$$

For 'freeway', the safety awareness index explicitly derived as

$$sa_a = e^{-18.05} \times \mathrm{AADT}_{a,\text{One direction}}^{0.98} \times L_a.$$

The safety awareness indexes are used in the following user equilibrium model to determine the rational route choice for individual travelers that minimizing their own . Also, they are used in the following system optimal model to determine the collaborate routing that minimizes total predicted crashes.

4 User equilibrium model minimizing individual user safety awareness

This section formulates a link-node network equilibrium model in user equilibrium, where each traveler minimizes his or her own safety awareness. In short, such a model is labeled as UE-SA. Traditional user equilibrium models mainly focus on the route choice behaviors minimizing users' travel time cost instead of safety awareness, which is labeled as UE-TT.

For link flow towards the destination node s, the route choice of travelers' is modeled in a complementarity form below

$$0 \leq v_{ij}^s \perp sa_{ij} + \pi_j^s - \pi_i^s \geq 0, \tag{1}$$

where π_j^s is the nodal potential from node j to the destination node s, which is the minimum safety awareness (average predicted number of accidents) along the way from node j to s for each individual traveler. Similarly π_i^s is the nodal potential from i to s. sa_{ij} is the safety awareness index on link (i, j), which is due to traffic towards all destinations on link (i, j).

The above complementarity suggests two implications.

1)If there are travelers choosing to traverse link (i, j) (i.e., link flow is positive $v_{ij}^s > 0$), then traversing on link (i, j) is the choice minimizing the safety awareness from node i to destination s, i.e., the safety awareness traversing through link (i, j): $sa_{ij} + \pi_j^s$ equals the minimum safety awareness from node i to s: π_i^s.

2)If the safety awareness traversing through link (i, j) is higher than the minimum from node i, then there is no traveler choosing link (i, j), i.e., if $sa_{ij} + \pi_j^s > \pi_i^s$ then $v_{ij}^s = 0$.

Besides the complementarity constraints for every link destination pair, there are flow conservation constraints as well as the definition of safety awareness for types of links to complete the UE-SA model.

The flow conservation at node i for destination s is denoted as follows, which covers the flow coming into node i, demand generated at node i, and the flow going out of node i.

$$\sum_{j \in \mathcal{N}} v_{ij}^s = \sum_{k \in \mathcal{N}} \Big(v_{ki}^s + D_{os} \tag{2}$$

The definitions of safety awareness on different types of links are different, as discussed in the previous section. For 'freeway', the safety awareness is only related to the flow on the same link, which is defined as

$$sa_{ij} = e^{-18.05} \times \left(\sum_s v_{ij}^s \right)^{0.98} \times L_{ij}. \tag{3}$$

For 'multilane', the safety awareness is related to the summation of flow on the same link and the link with the opposite direction. To simplify the modeling, we assume the pair of bi-directional links share the same link length, i.e., $L_{ij} = L_{ji}$. The safety awareness for 'multilane' is defined as

$$sa_{ij} = e^{-9.14} \times \left(\sum_s v_{ij}^s + \sum_s v_{ji}^s \right)^{0.07} \times L_{ij}. \tag{4}$$

The UE-SA model is composed by Eqs (1), (2), (3) and (4). The resulting system is a nonlinear complementarity problem and can be solved with the PATH solver (Ferris and Munson).

5 System optimum model minimizing total user safety awareness

This section formulates a system optimal traffic assignment SO-SA, which indicates the best performance benchmark that travelers cooperate to minimize the total safety awareness in the network.

The definitions of link safety awareness and the flow conservation in So-SA follow Eqs (3), (4) and Eq (2), respectively. The major difference between UE-SA and SO-SA is on the route choice behavior. In UE-SA it is assumed that each individual traveler are rational and miminizes their own safety awareness in the route choice; while in SO-SA, it is assumed that all travelers have the same goal to minimize the system total safety awareness instead of individual ones. Such a different assumption on route choice eventually lead to a nonlinear optimization problem for SO-SA, instead of its counterpart in UE-SA, which is a feasible problem in nonlinear complementarity problem.

The nonlinear optimization problem of SO-SA is to minimize the objective function as the total safety awareness in the entire network, which is noted as

$$\min_{v} \sum_{(i,j)} sa_{ij} \cdot \sum_{s} \left(v_{ij}^{s} \right) \tag{5}$$

subject to Eqs (3), (4) and Eq (2), and $v_{ij}^s \geq 0$.

SO-SA can be solved by generic commercial nonlinear solvers. In this study, we apply the open-source solver IPOPTH, which is designed to deal with large-scale nonlinear programming, to solve such nonlinear optimization problems.

6 Numerical examples and analysis

In this Section, three network settings are solved for both UE-SA and SO-SA. For comparison purpose, the results of traditional UE and SO models concerning travel time only are also provided. For the tradition travel time aware scenarios, we use the BPR function to calculate the link travel time, where travel time on link (i,j) is $tt_{ij} = 0.15\left(1 + C_{ij}^{-1} \cdot \sum_s \left(v_{ij}^s\right)^4\right)$.

6.1 The simple network with three nodes

The first network setting is composed by three fully connected nodes, as shown in Figure 1

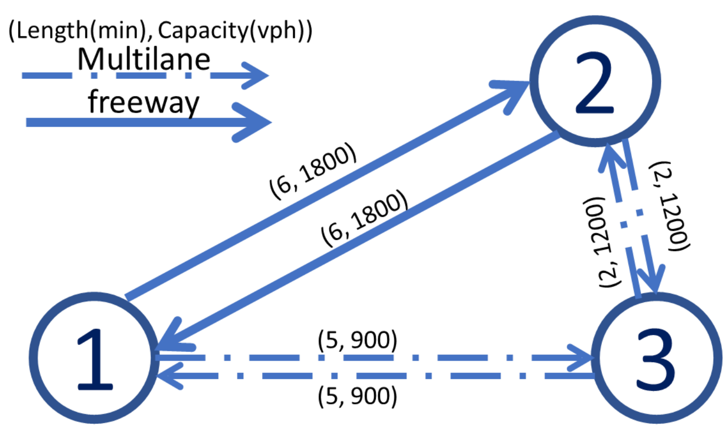

Figure 1: The simple network with three nodes with link parameters

The demand profile for this numerical example is of light traffic demand. There are two origin-destination pairs (1,3) and (3,1). There are 3,000 travelers from node 1 to 3, and 500 travelers from 3 to 1. Nodes 1 and 2 are connected by freeway, and other road segments are multilane.

If travel time was the only consideration by the users, for this light traffic scenario, it is expected that significant portion (if not all) of demand from node 1 to 3 would choose link 1-3, and demand from node 3 to 1 would choose link 3-1, as they have less free-flow travel time and therefore likely less travel time with light traffic. However, for the safety-aware travelers, it may not be the case necessarily.

Table 1: Link flow results of four different problems for the simple network with three nodes

Link Flow	1-2	1-3	2-1	2-3	3-1	3-2
UE-SA	2995	5	500	2995		500
UE-TT	1593	1407		1593	500	
SO-SA	2834	166	500	2834		500
SO-TT	1752	1248		1752	500	

Table 1 lists the detailed link flow for all links for 4 problems, namely the safety awareness user equilibrium (UE-SA), travel time user equilibrium (UE-TT), system optimal safety awareness (SO-SA) and system optimal travel time (SO-TT).

It is found that the safety-aware scenarios (UE-SA and SO-SA) tend to route the demand from 1 to 3 onto the route 1-2-3 predominantly, and route all demand from 3 to 1 onto the route 3-2-1. On the other hand, the travel time aware scenarios (UE-TT and SO-TT) tend to split more evenly the OD demand from 1 to 3 onto two routes 1-2-3 and 1-3, while route all demand from 3 to 1 onto the route 3-1.

The significant gap on the routing results between the safety aware scenarios and travel time aware ones can be explained by the definitions of the safety awareness. In general, freeways tends to achieve much lower predicted number of accidents per travelers especially for light traffic, because the intercept coefficient is much smaller. It is observed from the UE-SA results that the safety awareness on the multilane link 1-3 ($sa_{13} = 6.02 \times 10^{-4}$) is almost three times of that on the freeway link 1-2 ($sa_{12} = 2.22 \times 10^{-4}$), even though link 1-3 is even shorter than link 1-2. At the user equilibrium, both the routes 1-2-3 and 1-3 share the same safety awareness for individual travelers at ($sa_{12} + sa_{23} = sa_{13} = 6.02 \times 10^{-4}$). The demand from 3 to 1 finds that traversing through the route 3-2-1 can achieve less safety awareness ($sa_{32} + sa_{21} = 4.18 \times 10^{-4}$) than traveling on link 3-1 ($sa_{31} = 6.02 \times 10^{-4}$). Therefore, all OD demand from 3 to 1 are assigned to route 3-2-1 in UE-SA. The total safety awareness in the network is 16.06 for UE-SA, which means the yearly predicted number of crashes in the network is slightly above 16.

SO-SA further reduces the total safety awareness by 5.36% from UE-SA by diverting some traffic from route 1-2-3 onto route 1-3. However, by doing so, SO-SA increases the inequity on safety awareness. The resulting routing by SO-SA increases the safety awareness for travelers on route 1-3 from 6.02×10^{-4} in UE-SA to 7.67×10^{-4} in SO-SA, while decrease the safety awareness for travelers on route 1-2-3 from 6.02×10^{-4} in UE-SA to 5.89×10^{-4} in SO-SA. It is interpreted that the SO-SA routing increases the accident risks by 27.4% for about 5.5% travelers (166 of 3000) from 1 to 3, so that the majority 94.5% travelers from 1 to 3 have their accident risks reduced by 2.2%. From the system perspective, such reassignment of traffic benefit the entire system, as the total accident risks are reduced by 5.36%. However, these traffic flow reassigned from route 1-2-3 to 1-3 may see themselves suffer even more accident risks, as they may directly compare the safety awareness between themselves and the travelers still on route 1-2-3, rather than that in UE-SA. So that the increment of accident risks may be interpreted by these travelers as $(7.67 - 5.89)/5.89$, i.e., a whooping 30.2% increase on accident risks. This implies that the implementation of SO-SA should consider the inequity issues and make compensation to the travelers who need to shift their route choices.

Table 2: System performances of four different problems for the simple network with three nodes

	Total travel time	+% from UE-TT	Total safety awareness	+% from UE-TT
UE-SA	4.659707E+05	50.09%	16.059599	-33.30%
UE-TT	3.104552E+05	-	24.077293	-
SO-SA	3.849105E+05	23.98%	15.199581	-36.87%
SO-TT	3.100442E+05	-0.13%	24.073590	-0.02%

Table 2 shows two system performance indicators, total system travel time and total system safety awareness from the results of all four different problems for the simple network with three nodes. By treating the travel time aware user equilibrium (UE-TT) as the base case, the percentage of increase/decrease of the system indicators are listed. Compared with UE-TT, it is found that

1) UE-SA reduces the system predicted crashes by 33.3% with a 50.09% increase of total travel time.

2) SO-SA reduces the system predicted crashes by 36.87% with a 23.98% increase of total travel time.

3) SO-TT reduces the system predicted crashes by a marginal 0.02% with a marginal 0.13% reduction of total travel time.

6.2 The four-node network

The second network setting is composed by four fully connected nodes, as shown in Figure 2

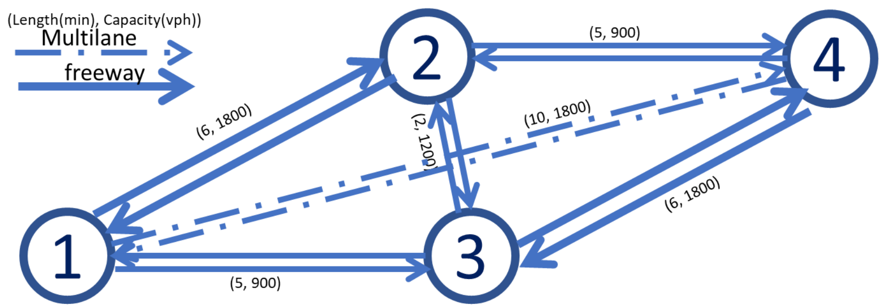

Figure 2: The four-node network with link parameters

Note that in this network, the only pair of multilane links are between nodes 1 and 4. Other links are all freeways. The demand profile for this numerical example is of heavy traffic demand, in contrast with the previous numerical example. There are three origin-destination pairs (1,4), (2,4) and (4,1). The demand are highly unevenly distributed, as the most volume is generated from node 1 to 4 with 30,000 travelers, while from 2 to 4 there are 5,000 travelers, and from 4 to 1 there are 5,000 travelers.

The inequity of safety awareness among travelers with the same OD pair for this numerical examples is summarized below. For the OD pair 1 to 4, there are 5 feasible routes, while the utilized routes are four, which are 1-4, 1-2-4, 1-3-4, 1-2-3-4. Among these utilized routes, route 1-4 has the highest safety awareness 2.105×10^{-3}, while the other three routes have the common safety awareness 1.138×10^{-3}. The relative difference of the safety awareness is as high as 85% for OD pair 1 to 4. For OD pair 4-1, routes 4-3-1, 4-2-1, 4-2-3-1 are utilized, which share the common safety awareness 3.4×10^{-4} so that there is no inequity of safety awareness for OD pair 4-1. It implies that the inequity of safety awareness may not necessarily span the entire network but may only appear for certain OD pairs.

Table 3: System performances of four different problems for the four-node network

	Total travel time	+% from UE-TT	Total safety awareness	+% from UE-TT
UE-SA	3.319570E+09	844.32%	63.723956	9.51%
UE-TT	3.515292E+08	-	58.191389	-
SO-SA	4.158773E+08	18.31%	53.840033	-7.48%
SO-TT	3.515256E+08	0.00%	57.810363	-0.65%

Table 3 shows two system performance indicators, total system travel time and total system safety awareness from the results of all four different problems for the four-node network. By treating the travel time aware user equilibrium (UE-TT) as the base case, the percentage of increase/decrease of the system indicators are listed. Compared with UE-TT, it is found that

1) UE-SA increases the system predicted crashes by 9.51% with a much undesired 844.32% increase of total travel time.

2) SO-SA reduces the system predicted crashes by 7.48% with a 18.31% increase of total travel time.

3) SO-TT reduces the system predicted crashes by a marginal 0.65% with a barely reduction of total travel time.

The comparison results for the four-node network with heavy traffic demand appear significantly different between UE-SA and UE-TT problems. In this example, UE-SA fails to reduce the system predicted crashes, compared with other results. In fact, in term of system predicted crashes (or equivalently total safety awareness), UE-SA performs the worst. It is a seemingly paradox that when everyone concerns their own safety awareness, the system safety becomes worse in total. Looking into the detailed link traffic flow, one can find that in UE-SA most travelers avoid the multilane link 1-4, so that they push both the safety awareness and travel time on other links high. The SO-SA scenario reassign many travelers to utilize the multilane link 1-4, so that both travel time and safety awareness for the entire network get reduced. Such observation implies that for safety aware travelers, adding a shorter yet low level road alternative may not necessarily benefit the system, since the safety aware travelers may not be attracted to utilize such alternative due to its low road level (i.e., large coefficients in predicted number of crashes).

6.3 The Sioux Falls network

The third network setting is the widely tested Sioux Falls network, composed by 24 nodes and 76 links, as shown in Figure 3

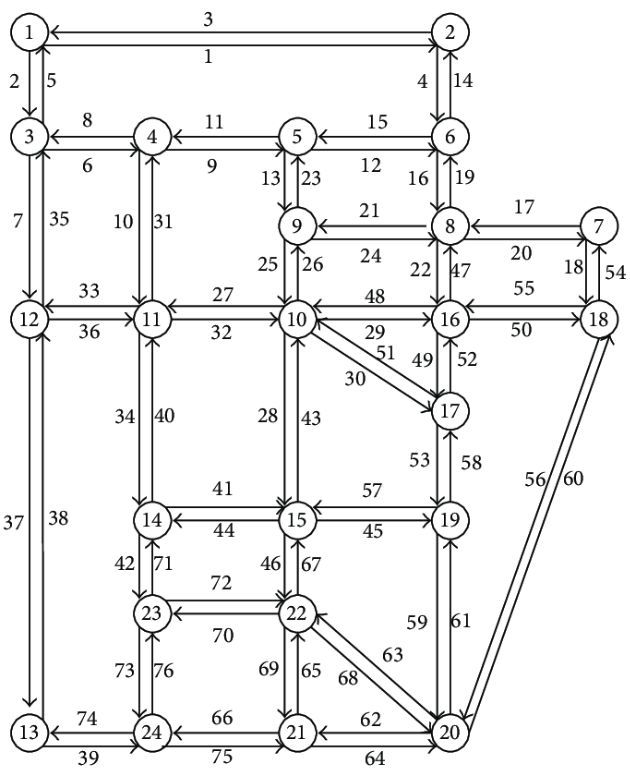

Figure 3: The Sioux Falls network with node and link numbers

There are 4 corner nodes selected to be the destination nodes- Nodes 1, 2, 13 and 18. The detailed link parameters and demand profiles can be found in the Appendix.

Four problems are successfully solved by the corresponding solvers for the Sioux Falls network. Table 4 summarizes the results. By treating the travel time aware user equilibrium (UE-TT) as the base case, the percentage of increase/decrease of the system indicators are listed. Compared with UE-TT, it is found that

1) UE-SA decreases the system predicted crashes by 19.4% with a 169.51% increase of total travel time.

2) SO-SA reduces the system predicted crashes by 19.79% (slightly better than UE-SA) with a 124.61% increase of total travel time.

3) SO-TT reduces the system predicted crashes by a marginal 2.15% with a marginal reduction of total travel time by 3%.

Table 4: System performances of four different problems for the Sioux Falls network

	Total travel time	+% from UE-TT	Total safety awareness	+% from UE-TT
UE-SA	8.350449E+04	169.51%	2.014124	-19.40%
UE-TT	3.098438E+04	-	2.498925	-
SO-SA	6.959524E+04	124.61%	2.004327	-19.79%
SO-TT	3.005582E+04	-3.00%	2.445231	-2.15%

7 Conclusions

This report implemented the safety awareness indexes into consideration for link-node-based travelers' route choices. Such safety awareness indexes are associated with the average accident risk on each road segment on the travelers' routes, which was dependent on traffic volumes and road types.

The numerical findings from the three different network settings reveal that the safety awareness based user equilibrium and system optimal vehicle routing/traffic assignment are significant different from their counterpart with the consideration of travel time only. There are two major observations worthy discussions. First, it is observed that in order to realize the minimal safety awareness for the entire system, usually a portion of travelers are required to shift from routes with lower safety awareness to routes with a higher one. Such a shift can never occur with autonomous behavior changes, as the rational safety aware travelers tend to choose routes with lower accident risks. Such a shift also generates safety inequity issues, which may be more difficult to deal with by the operational agencies. For the travel time aware travelers, it is well known that the agencies can impose congestion pricing or give monetary incentives that equals to the marginal cost, which can convert between monetary and time costs by using value-of-time. However, for the safety aware travelers, it is less political acceptable to simply convert accident risks /safety awareness to/from monetary costs, and thus economic means such as 'safety pricing' or safety incentives should be carefully designed to have such a desired shift with respect to minimizing the system accident risks.

Second, it is observed that the user equilibrium for safety awareness (UE-SA) sometimes reduces system total safety awareness from its travel time counterpart (UE-TT), but with different network setting UE-SA could make the system total safety awareness worse off, compared with UE-TT or other problems. Such seemingly paradox reveals that when everyone concerns their own safety awareness, the system safety could become worse in total. The underlying reasoning is that safety aware travelers may avoid the multilane links, which have higher accident risks in general. By avoiding such road segments, safety aware travelers may concentrate too much on high level roads, and bring negative impact for the accident risks on such road segments, so that they may push both the safety awareness and travel time on other links high. Such observation indicates that the system performance in term of total travel time or total safety awareness could fail if it simply allows the safety aware travelers to freely make route choices purely based on their own safety awareness.

Future research may investigate traveler groups with various levels of safety awareness, and various priorities and weights on considering travel time cost and accident risks for their route choice behaviors. Future research may also extend to time-dependent variation of safety awareness in different time-of-day, so that the dynamic effects for the safety-aware travelers' choice behaviors including route choice and departure time choice, can be studied in a coherent way.

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Appendix

The demand profile for Sioux Falls network is listed in Table 5

The network parameters including link length, free-flow travel time, flow capacity and road type for each link in the Sioux Falls network is listed in Tables 6 and 7.

Table 5: Origin-Destination demand profile for the Sioux Falls Network

Origins	Destinations			
	1	2	13	18
1	0	100	500	100
2	100	0	300	0
3	100	100	100	0
4	500	200	600	100
5	200	100	200	0
6	300	400	200	100
7	500	200	400	200
8	800	400	600	300
9	500	200	600	200
10	1300	600	1900	700
11	500	200	1000	100
12	200	100	1300	200
13	500	300	0	100
14	300	100	600	100
15	500	100	700	200
16	500	400	600	500
17	400	200	500	600
18	100	0	100	0
19	300	100	300	300
20	300	100	600	400
21	100	0	600	100
22	400	100	1300	300
23	300	0	800	100
24	100	0	700	0

Table 6: The link parameters for the Sioux Falls network

Link (i,j)	Length	Free-flow travel time	Flow capacity	Road type
1.2	6	6	25900.2	2
1.3	4	4	23403.47	2
2.1	6	6	25900.2	2
2.6	5	5	4958.181	1
3.1	4	4	23403.47	2
3.4	4	4	17110.52	1
3.12	4	4	23403.47	2
4.3	4	4	17110.52	1
4.5	2	2	17782.79	1
4.11	6	6	4908.827	1
5.4	2	2	17782.79	1
5.6	4	4	4947.995	1
5.9	5	5	10000	1
6.2	5	5	4958.181	1
6.5	4	4	4947.995	1
6.8	2	2	4898.588	1
7.8	3	3	7841.811	1
7.18	2	2	23403.47	2
8.6	2	2	4898.588	1
8.7	3	3	7841.811	1
8.9	10	10	5050.193	1
8.16	5	5	5045.823	1
9.5	5	5	10000	1
9.8	10	10	5050.193	1
9.1	3	3	13915.79	1
10.9	3	3	13915.79	1
10.11	5	5	10000	1
10.15	6	6	13512	1
10.16	4	4	4854.918	1
10.17	8	8	4993.511	1
11.4	6	6	4908.827	1
11.1	5	5	10000	1
11.12	6	6	4908.827	1
11.14	4	4	4876.508	1
12.3	4	4	23403.47	2
12.11	6	6	4908.827	1
12.13	3	3	25900.2	2
13.12	3	3	25900.2	2
13.24	4	4	5091.256	1
14.11	4	4	4876.508	1
14.15	5	5	5127.526	1
14.23	4	4	4924.791	1
15.1	6	6	13512	1
15.14	5	5	5127.526	1
15.19	3	3	14564.75	1
15.22	3	3	9599.181	1
16.8	5	5	5045.823	1
16.1	4	4	4854.918	1
16.17	2	2	5229.91	1
16.18	3	3	19679.9	1

Table 7: The link parameters for the Sioux Falls network (cont'd)

Link (i,j)	Length	Free-flow travel time	Flow capacity	Road type
17.1	8	8	4993.511	1
17.16	2	2	5229.91	1
17.19	2	2	4823.951	1
18.7	2	2	23403.47	2
18.16	3	3	19679.9	1
18.2	4	4	23403.47	2
19.15	3	3	14564.75	1
19.17	2	2	4823.951	1
19.2	4	4	5002.608	1
20.18	4	4	23403.47	2
20.19	4	4	5002.608	1
20.21	6	6	5059.912	1
20.22	5	5	5075.697	1
21.2	6	6	5059.912	1
21.22	2	2	5229.91	1
21.24	3	3	4885.358	1
22.15	3	3	9599.181	1
22.2	5	5	5075.697	1
22.21	2	2	5229.91	1
22.23	4	4	5000	1
23.14	4	4	4924.791	1
23.22	4	4	5000	1
23.24	2	2	5078.508	1
24.13	4	4	5091.256	1
24.21	3	3	4885.358	1
24.23	2	2	5078.508	1