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Risk-based Approach for Vehicle Route-choice with Interacting Objectives

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Abstract

Vehicle Route-choice (VRC) is a topic of interest to many researchers while discussing moving people and goods from a point to another, subject to constraints such as time, cost, safety, and others. Most of VRC problems in the literature are deterministic and do not account for uncertainties in objective estimation. In addition, they consider only individual objectives in their cost function, neglecting the impact of their interactions. Thus, this study addresses the above gaps and proposes a VRC framework that acknowledges the risk nature of interacting objectives and driver preference in the total cost function of the problem, using an interactive approach called Choquet integral (CI). The cost function includes objectives of minimizing delay time, crash risk and air emissions, and is expressed in units of road users under risk due to the occurrence of these events. The proposed approach will be compared to the results of traditional weighted arithmetic mean (WAM) method in selecting the best route. The results showed no differences in route ranking between CI and WAM methods. However, the total cost value of the optimal route using CI was doubled compared to the one generated using WAM. Delay and crash risks have the greatest positive interaction in CI, which reveals that they interfere together greatly. That is, CI is a better approach to capture the consequences of interrelated events while formulating the problem objective function and hence gives more realistic results.

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Keywords: Vehicle route choice, Delay time, Crash risk, Air emissions, Choquet integral, Weighted arithmetic mean

1. Introduction

It becomes distinct that interference between the transportation system and our life has broad ramifications that go beyond the well-known vital purpose of moving individuals and goods from a point to another. Whereas there is no doubt that transportation has facilitated our daily activities in an extraordinary manner, much still need to be

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understood about the side impacts on the human health and surrounding environment. Many concerns are raising which focus on the effects of road infrastructure expansion on congestion of urban transportation system, air and noise emissions, risk of accidents, natural resources consumption, and the quality of life. Many solutions are becoming available, thanks to technology development, which helped in evolving the traditional means of vehicle routing activity.

Vehicle Route-choice (VRC) is one of the hot topics in the field of transportation engineering that aims to find optimal paths given some constraints. It is included in the functionality of many navigation systems and involves the use of algorithms to identify the optimized path from a selected origin to a destination pair within a network setting. People, in nature, are seeking to optimize their trip path by considering some travel objectives that reflect their preferences of minimizing the associated travel time, costs, energy or to obtain the maximum profits (Steg and Gifford, 2005).

Over time, VRC has evolved to becoming a multi-criteria problem in which many objectives, sometimes conflicting with each other, are considered simultaneously. Multi-objective optimization competes for the best solution in a space of choices where it is believed that there is no single solution, but a set of alternatives called Pareto-optimal solutions. An important task in multi-objective optimization is the recommendation of the most preferred solution which is aided by the decision maker. Previously, trip planning was confined to minimizing the travel time and/ or costs only. However, such behavior has led to many undesired consequences such as the increase in traffic congestion, fuel consumptions and accident risks. Therefore, there has been a great attention to account for traffic safety and green transportation concepts, besides minimizing the travel times and costs (Cassini, 1998; Fabiano et al., 2002; Litman and Burwell, 2006; Zografos and Androutsopoulos, 2008; Hill et al., 2009; Ullrich et al., 2010; Chakrabarti and Parikh, 2011; Pradhananga et al., 2013; Rahman et al., 2014). Throughout the consideration of objectives related to the economy, safety and environment in the VRC, one can say that the efforts embrace the sustainability of the transportation to reduce its negative consequences on the public health and environment.

In addition, there have been a great number of VRC researches in the literature, but the basic distinction is between deterministic (DVRC) and stochastic (SVRC) models (Bouyahia, 2018). The latter one is proposed to reflect the uncertainty in the problem where many cannot be exactly known in advance. As a result, various attempts have been shown to address the probabilistic or risk nature of VRC's objectives (e.g. travel time, customer demand, pickup and delivery, etc.) in different routing applications (Oyola et al., 2016; Oyola et al., 2017). However, most of these models explored only one stochastic aspect in the problem, except a few works. Additionally, many of the existing stochastic VRC models do not present the risk nature of the problem comprehensively, and they ignore the consideration of interacting objectives and their influence on the route-choice process.

In this paper, we propose a multi-objective VRC approach, from a passenger perspective, that considers both the risk nature of travel objectives and their interactions with each other. A total cost function is built, which includes objectives of minimizing the delay time of travel, crash occurrence and critical air emission rates, as well as their interactions. It is expressed in units of road users under risk due to the occurrence of the above events. A fuzzified approach called Choquet integral (CI), which captures the user's knowledge of a partial pre-order of such objectives to the problem, is utilized to combine the problem's objectives. This approach is compared to weighted arithmetic mean (WAM) method in terms of alternative route ranking and total cost values. As an application domain, we address the problem of route-choice on a real-life network set of Calgary City in Canada.

The remaining parts of the paper are as follows: section 2 is a summary of related works in the literature. Sections 3 and 4 are the proposed VRC problem definition and employed data description. Section 5 presents the proposed methodology of risk-based route choice approach with interacting objectives. Section 6 discusses the results found using CI and WAM methods. Concluding the remarks and study limitations are provided in the last section.

2. Literature Review

2.1. Objectives of VRC Problems

Most of the urbanized cities suffer from traffic delays on roads. The Bureau of Infrastructure, Transport and Regional Economics in Australia published an information sheet showing that the total delay costs trend across all Australian capital cities increased with 100% between years 2000 and 2015, and is expected to continue growing

(BITRE, 2015). This phenomenon is becoming unavoidable with the expansion of roadway infrastructure, which affects our daily business activities. Traffic congestion is the main cause of delay where the literature defined two types of congestion. The first one is called recurrent congestion, which depends on fluctuations in traffic flow throughout the day. The second type is non-recurrent congestion where external sources, such as crashes, are the contributing factors for its occurrence. In general, a delay time is assessed as money lost (e.g. individual time value and fuel consumption). Schrank and Lomax (2007) estimated the time cost of a traveler by $14.60 per hour. Accordingly, traffic congestions caused an additional 4.2 billion hours for travel, resulting in the consumption of an additional 2.9 billion gallons of fuel corresponding to a congestion cost of $78 billion in the USA. This is a serious figure that needs the attention and contribution from all concerned stakeholders, as well as the research and development sector. Some studies considered minimizing delay time in their VRC problems. For example, Pradhananga et al. (2013) aimed to minimize the sum of the population-based (i.e. risk to exposed population) and congestion-based risk cost (i.e. delay) resulting from truck transport in Japan. The results showed that the proposed model provides a better alternative to the conventional approaches as it gives compromised optimal solution avoiding routes that cause large increase of the congestion-based cost.

Moreover, traffic safety has increasing importance on the sustainability of the transportation system. It can play a significant role in advising road users to select their routes while maintaining other desired objectives. Nowadays, most of the driver's navigation systems rely on calculating the shortest paths considering the conventional criteria of minimizing trip time and/ or distance. Each road user has a degree of risk to be involved in a traffic crash when using a roadway facility. Thus, traffic safety-based objectives are highly recommended to be considered in VRC problems besides the other traditional ones (Sahnoon et al., 2017). There are a few attempts which considered traffic safety related objectives in their VRC problems. Conca et al. (2016) analyzed the inter-relationships between the frequency of accidents and traffic flow (i.e. Level of Service, LOS) in dangerous goods routing problem considering a traffic safety element. The developed cost function is a combination of travel time costs and the risk due to crashes. The results showed that at high population density areas, the cost of transport considering the traffic safety risk element has a minimum value at LOS (C), while for the less densely populated areas the variation of travel cost per kilometer between one LOS to another is minimum.

The environmental aspect is another theme that needs to be included in VRC problems to achieve sustainability on our roadway systems. Researchers have been looking for techniques to minimize the emissions of road vehicles and other transportation modes that have a direct relationship with global warming (Litman and Burwell, 2006; Hill et al., 2009). Vehicle emissions can directly impact human health the same as it does for the environment. Thus, many studies considered environmental-based objectives in solving VRC problems (Ahn et al., 2012; Yu-Qin et al., 2013; Demir et al., 2014). For example, Yu-Qin et al. (2013) examined the influence of minimizing air emissions objective on travelers' behavior of route-choice. The results proved that when drivers consider vehicle emissions factor in the route-choice objective function, exhaust emissions can be reduced by about 11.4% on the road network. Another study was conducted by Ehmke et al. (2108) to solve an objective function which combines driver and fuel costs, as well as travel time and distance in a delivery vehicle routing problem. They found that minimizing travel time can contribute to significantly higher fuel consumption than optimizing total costs, especially with a heterogeneous fleet.

2.2. Risk-based Vehicle Routing

The literature is rich with VRC problems that attempt to investigate multiple objectives in different vehicle routing applications (e.g. Pacheco and Marti, 2006; Demir et al., 2014; Molina et al., 2014; Kovacs et al., 2015). However, these objectives are kind of deterministic while in fact estimation of problem's objectives carry some degree of uncertainty (i.e. SVRC). In recent years, SVRC has become an interesting topic to reflect the intrinsic real-world uncertainty where many aspects cannot be known in advance. This has triggered several techniques to handle the imprecision of uncertain data in the problem. It is applied in the condition that the probability distribution of uncertain parameter is available according to reliable historical data (Faulin et al., 2011). As a result, risk assessment can be employed to assess the various impacts of the routing objectives on a traveler's route-choice. Risk-based analysis includes calculation of risks that take into consideration the occurrence probability of an event (i.e. incident), and its impact on the surrounding (i.e. consequences). Except for routing hazardous materials (e.g. Chakrabarti and Parikh, 2011; Pradhananga et al., 2013; Rahman et al., 2014; Sahnoon et al., 2016; Shankar et al., 2018), most of VRC studies found in the literature do not consider risk nature in the problem, which might be essential in the formulation of the objective function. Implicitly, drivers want to avoid high-risk roads but most of them are not aware of the nature of risks involved. Thus, the risk-based analysis can be integrated into a comprehensive measure accounting for objective estimation uncertainty, which can suggest more accurate results than the conventional deterministic approaches.

2.3. Choquet Integral Approach

Many multi-objective VRCs assume a specific mathematical model of user's preferences which searches for the most optimal solution. However, simple models such as the weighted sum of objectives fail, sometimes, to represent the best solution. Consequently, there is a tendency to adopt more advanced and complex approaches of choice ranking that are originated from indirect user preference, which has a form of pairwise comparisons of some solutions from the existing population of study (Branke et al., 2010; Branke et al., 2016).

Until recently, the weighted arithmetic mean (WAM) was the most common aggregation approach in multi-criteria decision-making problems with its well-known limitations. This drawback has been partially solved by using some interactive methods like Choquet Integral (CI). CI is defined as an aggregation function with respect to a fuzzy measure acting on the domain of all possible solution combinations of a set of criteria (Choquet, 1954; Grabisch, 1996). It is applied in some multi-objective problems, which integrate partial user's preferences, e.g. maximal and minimal trade-offs (Branke et al., 2001), or desirability functions (Wanger and Trautmann, 2010). This approach considers the interaction of the problem's main objectives that are "interrelated in nature". For instance, in case of crash occurrence, there is a high probability of traffic congestion formation upstream the crash point and thus a time delay is inevitable. One advantage of this method is that the problem owner has the chance to rank the objectives based on his/ her preference and give priority for some objectives over the others depending on the purpose of the trip. A commuter, for example, would choose to minimize delay time objective over the other ones if the trip purpose is home to work during the morning time.

The CI seems to be a candidate approach that can be examined in the current research where the studied objectives are interrelated in nature (e.g. crash occurrence and generation of delay time). Also, results generated using the CI approach in the current proposed VRC framework can be compared to the ones from WAM method to investigate the differences on route selection. Up to the authors' knowledge, there was no previous attempt in the literature to solve a VRC problem with risk-based interacting objectives using CI.

3. Problem Definition

3.1. Model

From a conceptual perspective, VRC can be modeled as a complete network $G = \{A, N\}$ where A is a set of a links and N is a set of n nodes. Each link $a_{ij} \in A$ has a tail node $i \in N$ and a head node $j \in N$. To travel between an origin o and destination d nodes, the vehicle uses a series of arcs, called a route R_{od}. Let us denote by $T = \{c_1, c_2, \ldots, c_k\}$ the cost associated to link a_{ij} where $c_{k,ij}$ represents the risk-based objective of category k. For the sake of simplification, let us assume that costs are symmetric, i.e. $c_{k,ij} = c_{k,ji}$, and there are no waiting times at the nodes, which are network junctions. In this paper, the total cost function $U(c|R_{od})$ of route R_{od} within the network G is a weighted objective function, also called cost function, of delay D_a, crash risk S_a, high air emissions E_a and their pairwise combinations $\{k,l\} \in B$ as shown in Equation 1.

$$U_{R_{od} \in G}(c|R_{od}) = \sum_{k \in T, a \in A} w(k).\, c_{k,a} + \sum_{\{k,l\} \subseteq T, a \in A} w(k,l).\, (c_{k,a} \wedge c_{l,a}) \tag{1}$$

Where $w(k)$ and $w(k,l)$ are the importance weights of objective c_k and pairwise objective combinations $\{c_k, c_l\}$, respectively; and $\wedge$ stands for the minimum operation. The above formula shows the CI structure of defining a multi-objective VRC based on fuzzy concept of interacting criteria. Note that the conditions presented in Equation 2 need to be stressed while applying the proposed model:

$$\begin{cases} \sum_{k\in T} w(k) + \sum_{\{k,l\}\subseteq T} w(k,l) = 1 \\ w(k) \geq 0, \quad \forall_k \in B \\ w(k) + \sum_{l\in B} w(k,l) \geq 0, \ \forall_k \in T, \ \forall_B \subseteq T|k \end{cases} \tag{2}$$

The unit of total cost function $U(c|R_{od})$ is expressed as number of road users (i.e. drivers and pedestrian) under risk of the occurrence of the delay, crash and critical air emission rates.

3.2. Research Questions

Our primary research question is how the CI method of interacting objectives and driver preferences influence the ranking of the alternative routes, as compared to the traditional arithmetic mean method (WRM) approach. The other question is whether the inclusion of interrelated objectives in the objective function is significant in route-choice process. The authors will address this question by investigating both methods while solving the VRC problem.

4. Data Preparation

A part of Calgary city road network in Canada was selected as a case study to implement the proposed methodology. Three different routes from an origin *o* (University of Calgary, UoC) to a destination *d* (Calgary International Airport, YYC) were chosen as alternative routes for the route choice decision-making problem (Figure 1). The three routes are named as: Route 1 (red color), Route 2 (black color) and Route 3 (blue color). These routes were determined as candidate paths since they are mostly chosen by drivers for the selected *o-d* pair. Each route was segmented into individual links with different geometric lengths, where the start and end of each link were determined wherever there is a change in number of lanes, cross-sectional geometry, traffic volume and speed limit.

The employed data in this study were collected at the individual links of the routes from the official open data portal and citizen dashboard (called Open Calgary: https://data.calgary.ca/), and covers a full year period of 2015. A total of 296 individual links were identified for the three routes in this study. The data are comprehensive with all required information such as average weekday traffic volume, posted speed limits, number of lanes, geometric road lengths and road classifications. It is worth mentioning that the source road links of the collected data did not match the exact boundaries of our segmented road links, as the latter ones were identified for the purpose of the current study. Thus, additional manipulation was performed to properly aggregate the data on each link. All spatial and attribute data analyses were performed within ArcGIS software as it is considered as a powerful geographical tool to deal with spatial data of large-scale network settings. A huge effort was put in preparing the study network and aggregating the raw traffic data on each link element. All prepared data will be employed in estimating the discussed risk-based objectives in the objective function. A summary of the link-based data descriptive statistics is shown in Table 1.

5. Methodology

In this section, we present the proposed methodology to evaluate the risk-based objectives on each link of a particular route and find the best route among the alternatives as shown in Figure 2. The first step is to estimate the risk-based objectives of delay, crash and critical air emissions events. Then, the importance weights of the objective function are determined by the CI method using pairwise comparisons of the objectives and route ranking. Finally, the optimal route is found, which corresponds to the least total cost value of minimum delay, crash risk and critical air emissions.

The current VRC problem was believed to be better presented with a decision tree as shown in Figure 3. The first left column is the set of alternative routes 1, 2 and 3 where each has either a single objective or a set of many objectives including the pairwise combination of objectives (column 2). Each objective set contains triggering variables that define the occurrence of an event associated with each objective. For example, the delay time is triggered when the link's actual travel time is greater than its free flow travel time. If so, a probability value is estimated using Monte Carlo simulation algorithm as will be discussed later in this section. The last column is the possible consequences of each objective set.

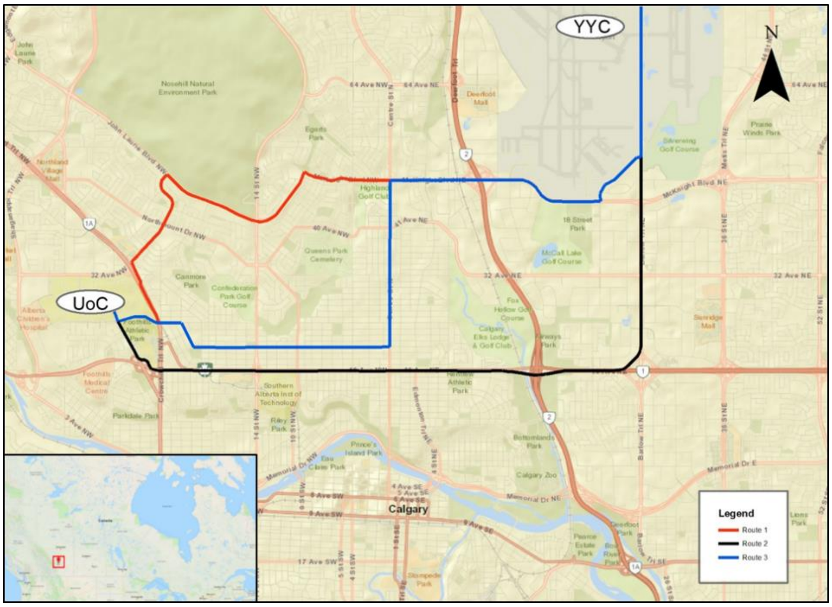


Fig. 1. Road network of Calgary City with the three alternative routes

Table 1. Descriptive statistics of the link-based data

Variable	Description	Min.	Max.	Mean	Standard Deviation
Traffic Volume	Average vehicle counts per typical weekday per link	100	174,000	34,418	22,648
Speed Limit	Posted speed limits per link (km/hr)	30	110	58.7	15.2
Number of Lanes	The number of lanes per direction of travel	1	5	1.4	0.67
Length	Geometric length of the road (meters)	13.5	17,531.5	543	922.4
Travel Time	Actual travel time in minutes	0.02	21.9	0.52	0.79
Crash Frequency	Average predicted annual crash frequency	1.36	14.83	3.23	1.26
Air Emissions Rate	Estimated CO_2 air emission rates (gram/ kilometer) per day	36.31	561.49	46.92	39.36
Road Users	The daily number of road users (drivers and pedestrian) in each road link	210	329,550	63,207	45,409

5.1. Formulation of risk-based objectives

5.1.1. Objective 1: Minimize delay risk

Delay time is defined as the difference between the actual travel time T_a and the free flow travel time t_a on a link a. It is a function of link's travel speed v_a, traffic demand V_a, and road capacity C_a, and is calculated using the Bureau of Public Roads (BPR) link performance function (Steenbrink, 1974) as shown in Equation 3. It was not possible to use the actual travel times from the source site, as the geometry of the segmented links were different than the ones existed in the source database. Therefore, the BPR is chosen to re-calculate the travel time on each route link a (Note: the waiting time at intersection n (t_n) is neglected in this study; the values of α and β are 0.15 and 4, respectively).

$$T_a = t_a \left[1 + \alpha \left(\frac{V_a}{C_a}\right)^{\beta}\right] + t_n \tag{3}$$

We can express the risk model of delay time objective on link a by including the probability and consequences terms as discussed earlier (Equation 4). Where $P(D_a)$ is the probability of delay occurrence and $P(Q_i|D)$ is the conditional probability of consequence Q_i occurrence given the existence of delay event.

$$c_{D,a} = P(D_a).\ \sum_{i=1}^{2} P(Q_i|D_a) * Q_i \tag{4}$$

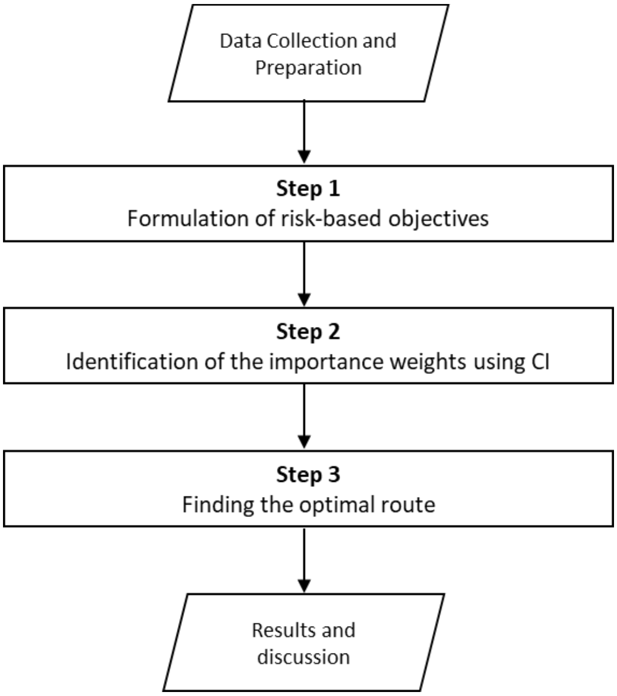


Figure 2: Conceptual framework of the proposed methodology

5.1.2. Objective 2: Minimize crash risk

Risk of crashes was determined using empirical estimation models of annual crash frequencies on each road link of Calgary city, as presented in reference (Abdelnaby et al., 2016). In our study, a threshold of three annual crashes was selected to identify a particular road link with a high crash frequency. This threshold is the annual average crash frequency in Calgary city during the study period. The crash risk objective estimation on link a is shown in Equation 5, where $P(S_a)$ is the probability of crash occurrence and $P(Q_i|S)$ is the conditional probability of consequence Q_i occurrence given the existence of a crash.

$$c_{S,a} = P(S_a).\ \sum_{i=1}^{2} P(Q_i|S_a) * Q_i \tag{5}$$

5.1.3. Objective 3: Minimize risk of critical air emissions

In fact, 'critical' vehicles' air emission rates (in grams per kilometer of road length) are typically observed at either low speed (below 50 km/hr) or high speed (above 80 km/hr) intervals (Barth and Boriboonsomsin, 2008). Since the alternative routes are urban, their speed limits were below 80 km/hr. Thus, the air emission rates are said to be critical when the travel speed is below 50 km/hr. Thus, vehicle's average travel speed is the triggering variable in estimating the associated risk of critical air emissions. The estimation of emission rates measure was inherited from Barth and Boriboonsomsin (2008) models. Then, this measure was extended to be risk-based using Equation 6, where $P(E_a)$ is the probability of critical air emissions occurrence and $P(Q_i|E)$ is the conditional probability of consequence Q_i occurrence given the existence of the event.

$$c_{E,a} = P(E_a).\ \sum_{i=1}^{2} P(Q_i|E_a) * Q_i \tag{6}$$

5.1.4. Probability of occurrence of triggering variables

The occurrence probability of delay, crash and critical air emission rates were based on analyzing triggering variables. These variables (X_i), i.e. actual travel times, estimated average annual crash frequency, and vehicles' average travel speeds, were first randomized by fitting them to suitable probability distribution functions (PDF). This is an essential step to account for any uncertainties in their measurements. The best PDF was determined through analysis of the empirical variable measurements at road links. MATLAB - Find Best Distribution tool was employed to manipulate the data fitting analysis and calculate the associated statistical parameters (i.e. mean and standard deviation). After that, the probability of occurrence was found using Monte Carlo Simulation (MCS) through conducting a large number of computerized experiments. The MCS steps are outlined as follows:

1. Sampling of random triggering variables; $X = (X_1, X_2, \ldots, X_n)$: generate samples that represent distributions of each triggering variable from their PDFs for a number M of generated samples.
2. Calculate $Y = g(X)$ for each objective related event: for example, a delay on link a exists if $T_a > t_a$. Therefore, if $Y = t_a - T_a \leq 0$, one can say that link a has a delay time since actual travel time is greater than free flow travel time.
3. Find an Indicator function $I(X)$ measure (Equation 7): this measure has a binary output; if $Y \leq 0$, $I(X) = 1$. Otherwise it is zero.

$$I(X) = \begin{cases} 1; if\ g(X)\ \leq 0 \\ 0; otherwise \end{cases} \tag{7}$$

4. Then, the probability of an event A occurrence is found as shown in Equation 8, where M is the number of generated samples of random variables.

$$P(A) = \bar{I}\,(\mathrm{x}) = \frac{1}{M} \sum_{i=1}^{M} I(x_i) \tag{8}$$

5.1.5. Risk consequences

The consequences of each risk-based objective are number road users that may arise as a result of event occurrence. The total number of road users on a certain link is defined as the total of vehicles' passengers (an average vehicle occupancy of 1.5 was assumed) and pedestrians during a typical weekday. Each event has two or more possible consequences, which carry a conditional probability value of occurrence $P(Q_i|A)$ as shown in Figure 3. In the event of a road crash, for example, injuries and/or fatalities may and may not be resulted. Each possible consequence has a probability of occurrence $P(Q_i|A)$, which is estimated using the multiplication rule of probabilities shown in Equation 9, where $P(A)$ is the probability of event occurrence and $P(Q_i \cap A)$ is the probability that outcome Q_i and event A happen at the same time. Since $P(A)$ was estimated using MCS with M generated samples, the conditional probabilities were consequently found.

$$P(Q_i|A) = P(Q_i \cap A)/P(A) \tag{9}$$

5.2. Identification of the importance weights using CI

After the risk-based objectives have been discussed in detail, their importance weights in the total cost function need to be evaluated before we proceed with the route-choice analysis. Recall that the proposed total cost function includes weights of interacting objectives, which were estimated using CI. Finding the weights of interacting objectives was based on partial ranking over a reference set of alternative solution and some semantical considerations about objectives. The input data for the weight finding problem are as follows (Marichal and Roubens, 2000):

- The set of route alternatives
- A table summarizing the risk-based objectives
- A partial pre-order on the set of alternatives and of objectives pairs

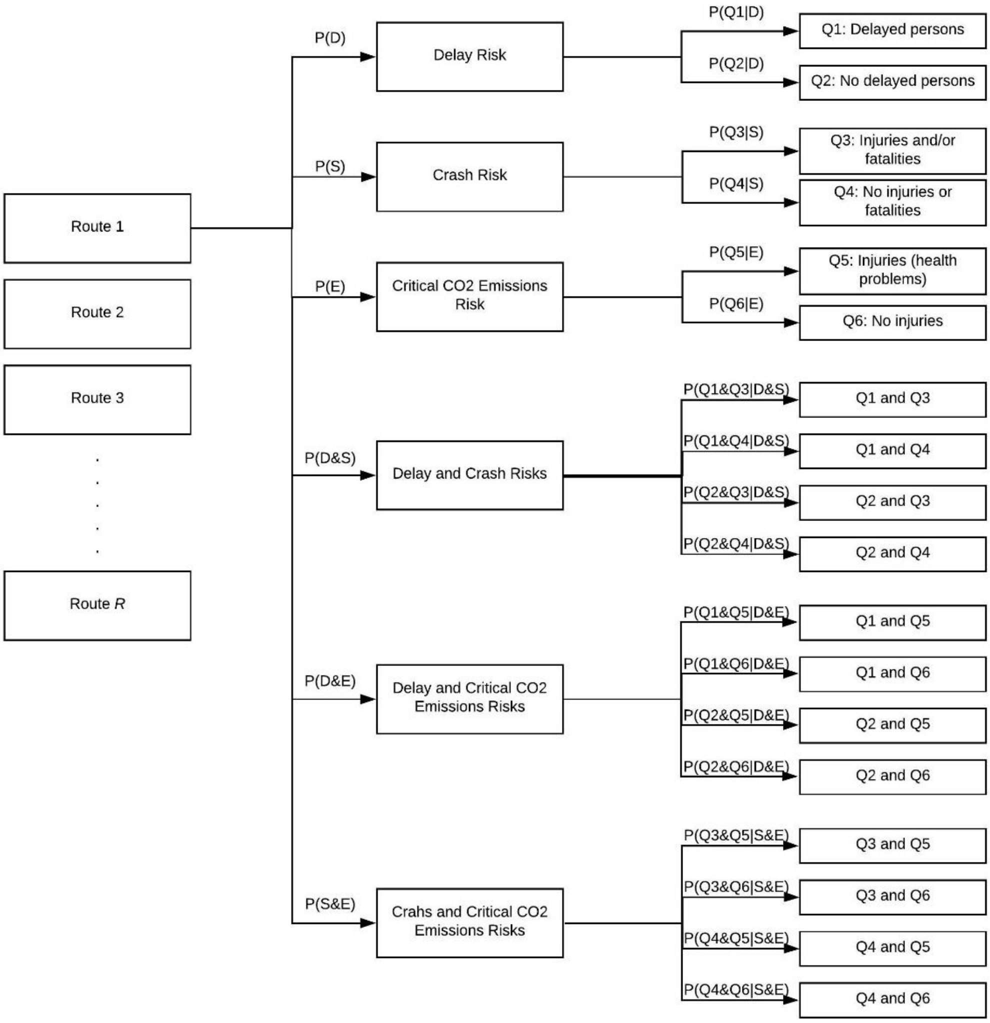


Figure 3: Decision tree of proposed stochastic route selection model.

Two scenarios were tested in this study, which reflect the user preference of one objective over the other (partial pre-ordering). The scenarios are as follows:

1 Scenario 1: Minimizing delay time objective is preferred over minimizing crash risk objective
2 Scenario 2: Minimizing crash risk objective is preferred over minimizing delay time objective

For each scenario, a ranking of the alternative routes (e.g. R_1, R_2, …, R_m, R_n,) was performed based on a favored objective c_k over the other. Then, the importance weights were determined by solving a system of inequalities

(Equation 10) that have the weights combined with pairwise comparisons of alternatives. A positive slack variable δ was introduced to the following general form of linear system to convert the strict inequalities to vague:

$$\begin{aligned}
&\text{Maximize } z = \varepsilon \\
&\text{Subject to} \\
&\textstyle\sum_{i=1,j=1}^{N} w(k,l).\left[c_{k,Rm} - c_{k,Rn}\right] \leq \delta \qquad (10) \\
&\sum_{k\in T} w(k) + \sum_{\{k,l\}\subseteq T} w(k,l) = 1 \\
&w(k) \geq 0, \quad \forall_k \in B \\
&w(k) + \sum_{l\in B} w(k,l) \geq 0, \qquad \forall_k \in T,\ \forall_B \subseteq T|k
\end{aligned}$$

The importance weights of WAM were subjectively assigned to represent the proposed ranking of scenarios 1 and 2. For instance, in scenario 1, the importance weight for delay time objective was higher than the one for the crash risk objective, and the weight for the crash risk objective is greater than the one for critical air emission.

Further, the level of interaction between objectives is also interpreted. The principle proposed by Shapley (1953) and Banzhaf (1964) of a coefficient of importance, called the importance index or value, was used to reflect the degree of interaction between the objectives. Marichal and Roubens (2000) stated that the CI method seems to be the most appropriate in many applications since it permits to model the interactions between objectives while remaining simple. The interaction indices of single and pairwise objectives are presented in Equations 11 and 12, respectively:

$$I(k) = w(k) + \tfrac{1}{2}\textstyle\sum_{j\in T|k}^{n} w(k,l) \qquad k \in T, \qquad (11)$$
$$I(kl) = w(k,l) \qquad k, l \in T, \qquad (12)$$

The signs of indices are illustrated as follows:

- When the interaction index is zero, the individual importance of the objectives adds up without interfering,
- If the sign is positive, a synergy effect between the objectives exists and they interfere in a positive way.

Then, the optimal route is calculated corresponding to the one with the minimum total cost value of the objective function. The route-choice analysis was performed four times using CI and WAM approaches for both scenarios 1 and 2.

6. Results and discussion

In this section, we present the results of the proposed methodology. Firstly, the empirical data of the triggering variables were analyzed to determine their best PDF distribution using MATLAB – Find Best Distribution tool. The best fit distributions were selected based on a statistical measure called Akaike information criterion (AIC). This measure estimates the relative quality of a PDF for a given set of data and provides a mean of selection. It is agreed that the preferred PDF is the one with the minimum AIC value. The log-normal (LN) distribution function was found within the best PDFs for all variables. The statistical parameters of the LN distribution (i.e. mean λ and standard deviation ζ) were also determined to initiate the MCS algorithm (Equation 8) for probability calculations. Due to the space limitation of the paper, an example of generated PDF for the actual travel time random variable is shown in Figure 4.

On the other hand, possible consequences were also estimated using the probability multiplication rule described earlier (Equation 9). An example of probability and consequences results for Route 1 is shown in Table 2. We can see that the probability of delay has a relatively higher proportion, compared to ones of the other events, which reflects that the selected routes witness busy traffic flows during the day. Additionally, when delay and crash risks were combined, their probability of occurrence did not exceed 20%. This can be justified as the higher the traffic density the lower the chance of a crash occurrence involving injuries and/ or fatalities. Furthermore, the conditional probabilities of their positive consequences (i.e. Delayed persons and injuries/ fatalities) have a higher occurrence value compared to the other combinations of consequences.

The above analysis was repeated for all routes to estimate the risk-based objective as shown in Table 3. It is obvious that Route 2 has the minimum risk values of all risk-based objectives.

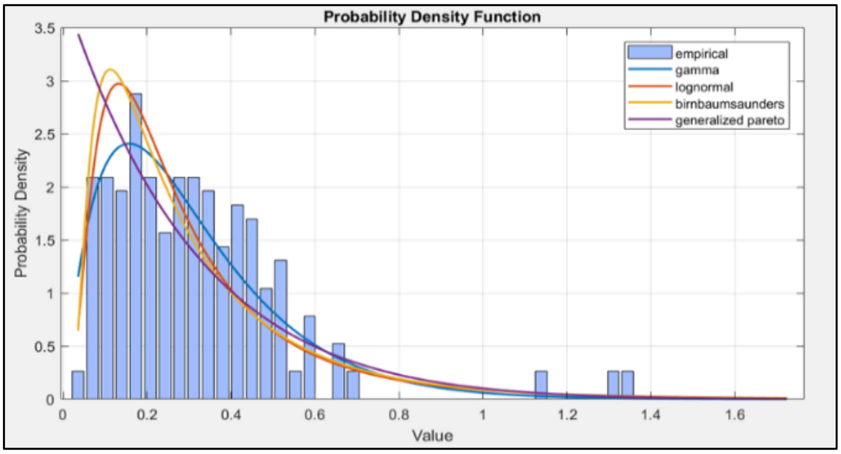


Figure 4: Best fit distributions for actual travel time random variable.

Table 2: Probability results using MCS

Event (A)	P(A)	Consequences (Q_i)	P(Q_i|A)
Delay	0.9685	Delayed persons (business activities)	0.9998
		No delayed persons	0.0002
Crash	0.2038	Crash injuries/fatalities	0.9907
		No crash injuries and fatalities	0.0093
Critical air emissions	0.2108	Injuries (Health problems)	0.9979
		No injuries (no Health problems)	0.0021
Delay and crash	0.1976	Delayed persons + crash injuries/ fatalities	0.9879
		Delayed persons + no crash injuries/ fatalities	0.0082
		No delayed persons + crash injuries/ fatalities	0.0038
		No delayed persons + no crash injuries/ fatalities	~0
Delay and critical air emissions	0.2052	Delayed persons + injuries (health problems)	0.9988
		Delayed persons + no injuries (no health problems)	0.0005
		No delayed persons + injuries (health problems)	0.0006
		No delayed persons + no injuries (no health problems)	0
Crash and critical air emissions	0.0436	Injuries from both risks	0.9996
		Crash injuries/ fatalities + no injuries (no health problems)	0.0003
		No crash injuries/ fatalities + injuries (health problems)	0.0001
		No crash injuries/ fatalities + no injuries (no health problems)	0

Table 3: Risk-based objective values for each alternative route

Route	Risk-based objectives (No. of people/ day)		
	Delay Risk ($x10^9$)	Crash Risk ($x10^7$)	Critical air emissions risk ($x10^7$)
R1	2.8719	12.740	13.780
R2	2.3751	6.1821	5.5838
R3	2.2539	9.2425	9.2496

The CI method can be applied by investigating the user preference of one objective over the other (partial pre-ordering). The two scenarios mentioned earlier were examined to test different user preferences in route selection. The first scenario is to prefer minimizing delay risk objective over minimizing crash risk (called Scenario 1) while the other scenario is to prefer minimizing crash risk over delay time objective (called Scenario 2). Also, the following reasoning was proposed for alternative routes ranking:

- When selecting a route with minimum delay, one may prefer to rank the crash risk objective over the critical air emissions risk, so R2>R3;
- When selecting route with higher crash risk, one may prefer to rank the delay risk over the critical air emission risk, so R3>R1;
- When the critical air emission risk is minimum, two scenarios are highlighted. One may prefer to rank delay over crash risk (i.e. R3>R1), otherwise R2>R3.

Then, the fuzzified importance weights were found by solving a linear programming system as illustrated in Equation 10. Using appropriate software, the weight sets for each scenario were obtained as shown in Figure 5. In addition, the interaction indices of each individual objective as well as their combinations, for both scenarios, are shown in Table 4. It can be seen that the only objectives interaction is between delay and crash risks, which reveals that they interfere together greatly.

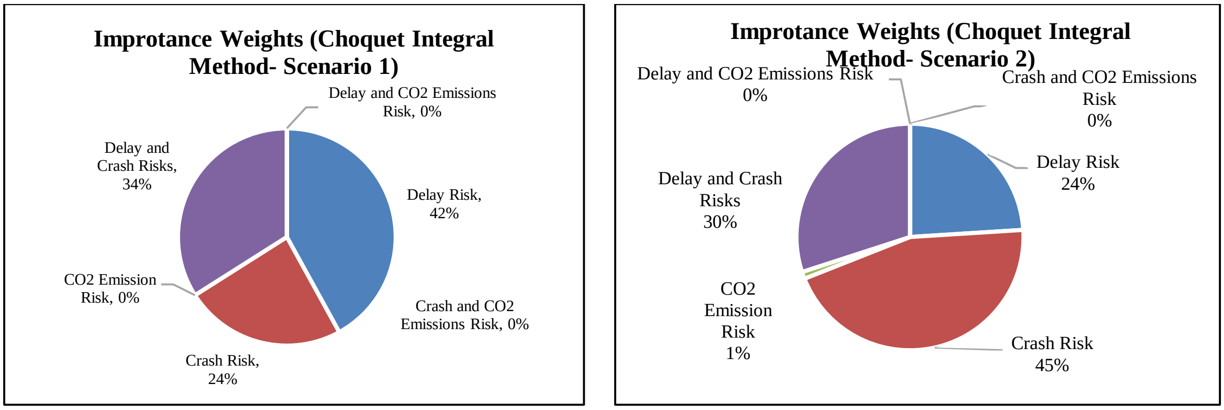
The total cost values for each alternative route, using the CI and WAM, were calculated and summarized in Table 5. We can realize that route R2 presides the first place among the other alternatives where it scored the minimum total cost value corresponding the lowest risk on road users. In addition, the ranking of the routes has not changed after using the CI compared to WAM. This can be due to one or more of the following reasons:

- The network size was not enough to conduct the route-choice analysis. Thus, a larger network scale may be needed to investigate the benefits of including interacting objectives in the objective function.
- Data accuracy and reliability is not high.
- The assumptions made in this study were not realistic enough (e.g. vehicle occupancy, road capacities, etc.)

On the other hand, the total cost values for R2 have increased by 118% and 60% for scenarios 1 and 2, respectively, after considering the interacting objectives using the CI method. This increase in risk units was believed to be reasonable for R2 counter to the other alternatives. R2 is one of the busiest urban roads in Calgary city, in fact, it is part of Trans-Canada highway, which links major cities in the country from British Columbia to Quebec provinces. Thus, if an accident happens at any point along the route, there is a high chance of congestion creation upstream the crash point. As a result, existing road users at that time will be under risk of being delayed and/or involved in an injury and/or fatality case due to the crash. That is, the CI is a better approach to capture the consequences of interrelated events while formulating the problem objective function, and hence gives more realistic results.

To further support the above justification, a paired t-test was conducted to state if the total cost values of CI and WAM approaches for scenario 1, as an example, are significantly different. This test is excellent to compare two different methods when the measurements are applied to the same subjects (i.e. routes in our case). For this test to be valid, the data sample needs to be normally distributed. Thus, Shapiro-Wilk normality test was performed on samples of 100 readings, for each method and at each route, using Statistical SPSS software. Two hypotheses were tested: H0 is the null hypothesis, which states that there is no difference between the distributions of sample data and normal distribution, while H1 is the alternative hypothesis, which is opposite to H0. It was found that all data samples of total costs of CI and WAM were normally distributed (p-value >0.05), as we failed to reject the null hypothesis of the test.

After that, data samples for each route and calculation approach were compared using paired t-test hypothesis testing. It was proved that the results obtained using CI were statistically different to the ones found using WAM (p-value < 0.05), as the null hypothesis of the test was rejected. The reasons why and how both results were different are out of this study scope, but it will be the topic of discussion in further studies.



(a) Importance weights of interacting objectives (Scenario 1)

(b) Importance weights of interacting objectives (Scenario 2)

Figure 5: Importance weights generated by the method of Choquet integral considering (a) scenario 1 and (b) scenario 2.

Table 4: Interaction indices results for both scenarios

Objective	Interaction index	
	Scenario 1	**Scenario 2**
Min. delay risk	0.59	0.39
Min. crash risk	0.41	0.60
Min. critical air emissions risk	0	0.01
Min. delay and crash risk	0.34	0.3
Min. delay and critical air emissions risk	0	0
Min. crash and critical air emissions risk	0	0

Table 5: Total cost values of alternative routes at each scenario (values are multiplied by 10^7)

Route	Choquet integral method		Weighted arithmetic mean method	
	Scenario 1	**Scenario 2**	**Scenario 1**	**Scenario 2**
R1	7.0292	9.3775	7.3067	9.8572
R2	3.4351	4.5305	1.5738	2.8326
R3	5.0078	6.5300	5.0167	6.6435

7. Conclusion

This study proposed a methodology for vehicle route-choice (VRC) with the consideration of risk-based interacting objectives and driver preference in the total cost function of the problem. It accounts for problem uncertainties in estimating the objectives of three different aspects of sustainable transportation; traffic efficiency, safety and environment. Also, as the objectives are interrelated in nature, their combinations were included in the objective function using Choquet integral (CI) method, and the route ranking was compared to the traditional weighted arithmetic mean (WAM) approach. The optimal route corresponds to the one with the minimum total cost, which is expressed in units of road users under risk due to the occurrence of the discussed events. The proposed methodology was applied on selected alternative routes of Calgary road network in Canada.

The results showed no difference in the ranking of the route alternative of CI and WAM methods, where route 2 was found as the best among the others. On the other hand, the total cost values were increased by 118% and 60% for scenarios 1 and 2, respectively, by considering the interacting objectives using CI method. This was justified as route 2 is one of the busiest urban roads in Calgary city where it is part of Trans-Canada highway, so combining the individual objectives has an influence on the total cost results. Moreover, it was found that the interrelated delay and crash risks have the greatest positive interaction, which reveals that they interfere together greatly. Paired t-test was conducted to prove that the results of CI are significantly different than the ones obtained using WAM at 95% confidence interval.

The authors believe that this study is a first step for consideration of interacting objectives in VRC problems, especially the ones that are interrelated in real-life. The proposed methodology may reveal different results of route ranking when applied on a larger network scale or using real-time data from road traffic sensors. Therefore, micro-analysis is required to investigate why results of CI and WAM are different from a transportation point of view.

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