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Multi-objective, risk-based approach for safe and sustainable vehicle routing

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Abstract

Vehicle routing is a daily activity to move people and goods from one point to another. Routing is subject to constraints, such as time, distance, and out-of-pocket cost. Traditionally, routing decisions were based mainly on efficiency considerations (i.e., finding shortest path in terms of distance or travel time). With rising global interest in traffic safety and green transportation, there is a need to consider other factors such as risk to humans and environment. In this study, a methodology was developed to provide a comprehensive, risk-based vehicle routing approach to account for various objectives (or risks), including: travel time, travel distance, travel cost, accident risk, air emissions risk, and noise risk. The methodology involves three major steps: first, estimation of the various risks for individual road links; second, integration of the individual risks into a single comprehensive risk measure using the Analytical Hierarchy Process (AHP); and finally, finding the preferred (i.e., least risky) route based on risk. The framework is implemented inside a Geographic Information System (GIS) environment. The proposed methodology was applied to a real-world setting: Sharjah City, United Arab Emirates. Outcomes are charted in the form of least-risky routes for a selected origin-destination pair taking into consideration each objective individually or in combinations, in addition to comprehensive risk. The proposed methodology provides a way to integrate environmental and safety related measures into vehicle routing, which is a step towards making the transportation system safer and greener.

Keywords – multi-objective vehicle routing, traffic safety, green routing, accident risk, risk-based routing, analytical hierarchy process, GIS

1. Introduction

Routing is a daily activity for many individuals and companies where it can be simply defined as moving people and goods from one point to another given some constraints (e.g., costs of travel). While some choose their routes based on shortest distance, others prefer to choose their routes based on shortest travel time or even out-of-pocket cost. Mathematically, routing problem is often considered an optimization problem with an objective to minimize the cost of travel. Travel distance or time were considered the only criteria used to determine the optimal (i.e., shortest) route. Overtime, vehicle routing analysis has evolved to becoming a multi-criteria challenge in which many factors besides the economical, traditional ones (e.g. travel time and distance) are considered. Thus, multi-objective routing is a problem of how to integrate multiple objectives, typically conflicting with each other, to find an optimal solution while considering all objectives simultaneously.

Because of global warming, there is an ever-increasing concern about the environmental impacts of transportation in general and individual and vehicle routing in particular. Researchers have been looking for techniques to minimize the emissions of road vehicles and other transportation modes. As a result, environmental factors need to be integrated into the routing problems in order to reduce the side effects of the global warming [1, 2]

In addition, traffic safety has an increasing importance in the transportation system. Based on the World Health Organization Global Status Report on road safety, the total number of road traffic deaths has plateaued at 1.25 million per year. This is a serious figure that needs to be highlighted through concerned traffic safety organizations world-wide. Thus, many authorities in the globe are implementing traffic strategies and awareness programs where relatively lower fatality rates are observed specially in high-income countries [3]. Given the improved public awareness on traffic safety, some road users are considering safer roads criterion for their daily travel besides the shortest path. Currently, most of the smart map navigation applications are considering the routes that gives minimum travel time, however; traffic safety must be integrated in the routing selection process to increase the traffic safety awareness to the public.

When planning travellers' trips, it has become necessary to have an approach that accounts for economic, environmental, and safety perspectives in vehicle routing collectively and not just individually. This paper proposes an innovative approach for the vehicle routing problem. It calls for estimating various risks (socio-economic and environmental impacts) of vehicle routing and integrating them into a single measure to be used for finding the least-risky route. The risk-based approach is proper since it translates the traffic related measures (e.g. travel time, safety, air emissions, etc.) into consequences on the surrounding environment along a travel route. It is worth mentioning that a survey was prepared to take the audience results regarding the importance of each objective over the another (i.e. pair-wise comparison) to help in the ranking of the problem's objectives that are used here into a single measure. To demonstrate the applicability of the proposed methodology, it was applied to a real-world case study, Sharjah City in the United Arab Emirates.

2. Literature review

Many studies have attempted to integrate economic, social, and environmental factors in the routing problem whereas multiple objectives can be considered together.

2.1. Multi-objective routing

Kovacs et al. [4] considered several objective functions for vehicle routing in the logistics industry. The independent objectives in their study were: improving driver consistency (i.e., minimizing the number of different drivers visiting the customers), arrival time consistency (i.e., minimizing the maximum difference between the earliest and the latest arrival time at each customer), and minimizing routing cost of the problem.

Ehrgott et al. [5] introduced three alternative approaches for combining multi-objective decision making with a stochastic user equilibrium model. The objective was to deduce a tractable, analytic method. The three methods were compared both in terms of their theoretical principles, and in terms of the implied trade-offs.

Molina et al. [6] proposed a multi-objective model based on Tchebycheff methods for vehicle routing problems. Three objective functions were minimized: total internal costs, CO_2 emissions, and other air pollutants such as NO_x. A heuristic algorithm was developed to solve the model when time windows are not considered. Results showed good quality solutions for the heuristic algorithm.

Another case study was introduced by Samanlioglu [7] where a multi-objective location routing model in the Marmara region of Turkey was developed. In this study, three objectives were minimized: total transportation cost of hazardous materials and fixed cost of treatment, disposal and recycling; total transportation risk to population along the route; and total risk to population around the treatment centers. A weighted formulation was developed and computed to find effective solutions to the problem.

Pacheco and Marti [8] applied a multi-objective optimization to find optimal routes for school buses. They minimized two objectives: the number of buses and the time a student would have to stay in the bus. The problem is represented by the service level (the maximum route length) and operational cost (the number of buses in the solution).

2.2. Green routing

A key environmental impact on human health is vehicle's air emissions. Until recently, the environmental impacts of travel were not considered during vehicle routing.

Jabir et al. [9] presented a multi-objective green vehicle routing optimization problem in which economic and environmental factors were considered. A hybrid algorithm combining an Ant Colony Optimization algorithm and a Variable Neighbourhood Solution was developed for finding the non-dominant pareto optimal solutions for the proposed problem. The main contribution of this study is in its flexibility to choose an appropriate solution from the set of solutions.

Demir et al. [10] presented an algorithm to solve a bi-objective pollution routing problem. The two objective functions considered were the minimization of fuel consumption and driving time. While several methods were tested, results showed that one method (called the hybrid method by the authors) is highly effective in finding good-quality solutions for the pollution routing problem.

Zhao et al. [11] have also contributed with a study in the field of green transport. They developed a model for estimating fuel consumption, carbon monoxide and nitrogen oxides emissions in the Buffalo-Niagara metropolis. Their results were found to be very close to the values calculated from a second model.

Yu-qin et al. [12] tested the influence of emission factors on travellers' behaviour of route choice. The results showed that the weight coefficient of travel cost impacts the drivers' behaviour. When drivers take emissions into account, exhaust emissions can be reduced by about 11.4% on a road network.

Ahn et al. [13] investigated the system-wide impacts of using eco-routing within large metropolitan where different scenarios were simulated and evaluated. The results of the simulation process showed that the eco-routed vehicles do not always save fuel consumption when compared to a typical user-equilibrium routing model. Further, the study showed that eco-routing does not necessarily reduce vehicle travel time or travel distance. It was concluded that when the eco-routing reduces fuel consumption levels, it also tends to reduce both travel time and distance, compared to the typical user-equilibrium routing.

Frey et al. [14] aimed at quantifying the variability in emissions of selected gasoline vehicles by routes, time of day, road grade, and vehicle. Field experiments on two origin-destination pairs were conducted and the results showed variations in vehicle emission from one route to another. The results showed that alternative routing can significantly impact trip emissions, especially when road grade was considered. Furthermore, the results showed a 24% difference of NO emissions when compared to alternative routes and a 19% difference when comparing congested travel time route with less congested one.

Another vehicle emission which could also impact humans is noise. The main effects of noise include disturbance (such as distraction, speech interference, and sleep disturbance) and annoyance. While numerous models exist to predict noise levels from roadway traffic, consideration of noise in vehicle routing has been largely overlooked.

2.3. Risk-based routing

Risk assessment approach can be utilized to assess the various impacts of the routing problem. Risk-based analysis includes calculation of risks that takes into consideration the occurrence probability of an event (e.g. incident), its magnitude (severity), and impact on its surrounding environment. There are many examples for utilizing risk-based models in routing hazardous material (HAZMAT).

Sahnoon et al. [15] developed a risk-based geographic information system (GIS) model for finding the least-risky routes for HAZMAT shipments. The proposed model combines multiple risks using importance weights into a single, comprehensive travel risk factor. The risks considered in the model include: travel time, travel distance, risk to exposed population, and risks due to traffic air and noise emissions. The results showed that using such a comprehensive model led to results that were very close to the traditional routing while accounting for safety and environmental aspects of HAZMAT vehicle routing.

Rahman et al. [16] proposed a bi-objective optimization model satisfying both risk and cost aspects of HAZMAT routing. In this model, one objective is to enhance network security by reducing the associated risk from movement of HAZMAT while the other one is to minimize the associated cost along the path to transport such materials. The model can therefore be used to compare alternative routing strategies to achieve a desired balance between risk and routing convenience.

Pradhananga et al., [17] discussed a methodology to minimize the sum of the population-based (i.e. risk to exposed population) and congestion-based risk cost (i.e. delay) from HAZMAT transport in Japan. The problem was solved using Ant Colony System-based algorithms and was compared to the case where each objective is to be taken solely. The comparison showed that the proposed model provides a better alternative to the conventional population-based model as it gives compromised optimal solution avoiding paths that causes large increase of the congestion-based cost.

Chakrabarti and Parikh [18] estimated the total risk of transporting hazardous materials (HAZMAT) in Indian state highways. Risk assessment of the problem includes: accident rate, average daily traffic, and surrounding population. Site specific values of accident rates and material spillage probabilities for different highway types were estimated. The study highlighted the evaluation of route-based calculation of total risk.

To sum up, the literature review revealed that researchers have attempted to combine several objectives into a single measure for solving the vehicle routing problem in various application areas. In addition, some studies discussed optimization of routing of vehicles carrying hazardous materials while considering the potential risk on the surrounding population. Further, some environmental-based factors were also considered in optimizing the vehicle routing problem - hence called green routing - motivated by the global interest in sustainable transport solutions. While most drivers select their routes merely based on the shortest travel time or distance, other aspects such as traffic safety and environmental impacts are generally overlooked when drivers make their travel decisions. Except for routing hazardous materials, most of the studies found in the literature do not consider the nature of risk through inclusion of the probability of occurrence. For example, a road with relatively high traffic demand has a higher accident probability and hence poses a higher risk. Implicitly, the drivers want to avoid high-risk roads but most of them are not aware of the nature of risks involved.

While previous studies addressed a variety of environmental-related objectives in addition to economical ones, the need for a more comprehensive approach in which multi-objective, risk-based criteria can be integrated into a comprehensive measure accounting for traffic safety (i.e., accident risk). Such an approach expands the routing problem from focusing on economic factors to a more comprehensive one accounting for various social and environmental impacts (i.e., sustainable transport). This study proposes developing a comprehensive, risk based travel cost function for general vehicle routing that considers the three bottom-line aspects of sustainability: economic, social, and environmental.

The considered risk-based objectives include: travel time, travel distance, travel cost, accident risk, air emissions risk, and noise risk. Assessing each of these objectives was achieved through utilizing a general risk model that accounts for the probability of occurrence, a response or resistance factor, and the impacted population.

3. Methodology

Figure 1 shows the conceptual framework of the methodology proposed in this study. The methodology involves three major steps: first, estimation of the individual risks for road network links; second, integration of the individual risks into a single comprehensive risk measure using the Analytical Hierarchy Process (AHP); and finally, finding the preferred (i.e., least risky) route based on risk using the shortest path algorithm in GIS, as described below.

3.1. Estimating the various risks

The proposed methodology allows for utilizing as many objectives (thereafter called risks) relevant to the vehicle routing problem as needed. Risk is probability of a negative impact associated with the route choice. Examples of the risks considered in this study include: travel time risk, travel distance risk, travel cost risk, accident risk, air emissions risk, and noise risk. The proposed methodology allows combining objectives/risks that affect route choice. The methodology is flexible as it can address as many objectives as needed, depending on the objectives of interest and availability of data.

To compute the various risks, the following general risk model is used in this study:

$$Risk = Risk\ Agent\ Dose \times Response\ Factor \times Exposed\ Population \tag{1}$$

where: *Risk Agent Dose* is the force that can potentially affect exposed population; *Response Factor* relates the Risk Agent Dose to the degree of impact on an exposed individual; and *Exposed Population* can be human or environmental populations, or environmental quality in general, or business activity and infrastructure. Exposed population can be one individual, which corresponds in traffic assignment to User Equilibrium, or the entire affected population which corresponds to System Equilibrium.

The general risk assessment model is based on: (a) quantifying the dose of a risk agent that can potentially affect an exposed individual(s), such as noise or air pollutant; (b) establishing a response factor through assessing the relationship between the risk agent dose and the response of those exposed; and (c) estimating the exposed population, e.g. humans or environmental populations, business activity, or infrastructure. The following sub-sections describe the considered objectives (risks) and how to quantify them using the general risk model.

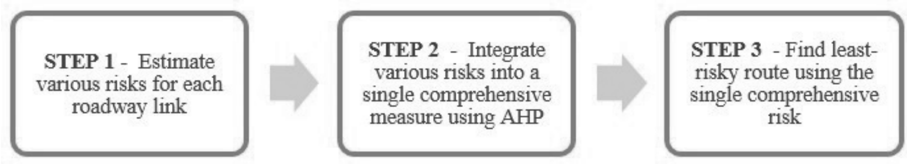


Fig. 1 - Conceptual framework of proposed methodology

3.1.1. Travel Time Risk

Reducing travel time and delay is a primary goal of all drivers. Therefore, travel time, including delay, can be considered as risk. This risk can impact the drivers themselves and the society at large due to loss of transportation efficiency. Based on the general risk model, travel time risk can be estimated as follows:

$$\textit{Travel Time Risk} = \textit{Travel Time} \times \textit{Travel Time Response Factor} \times \textit{Exposed Population} \quad (2)$$

where the *Travel Time,* including free-flow travel time and delays, is the risk agent/force; the *Travel Time Response Factor* is the impact of travel time or delay to different road users/ drivers depending on their trip purpose, and *Exposed Population* is mainly the road users/ drivers. The last two terms are assumed to be the same regardless of any route selected and as such they are discounted from consideration by making their values equal to one. Accordingly, the comparison between routes is based on travel time only. If actual travel times for roadway links are not known, then the travel time can be estimated using:

$$T_{v,a} = t_0 \left[1 + \alpha \left(\frac{v}{c}\right)^{\beta}\right] + t_{int} \quad (3)$$

where $T_{v,a}$ is travel time of vehicle v on link a; t_o is free-flow travel time on link a; v is flow on link a; c is capacity of link a; α and β are constants (in this study, the traditional values for α and β were used as 0.15 and 4, respectively); and t_{int} is delay time at each intersection. Different travel and delay times can be used depending on the time of the day.

3.1.2. Travel Distance Risk

Some drivers may prefer to use travel distance despite that the shortest path in terms of distance may not be the fastest one, especially when speed varies considerably. Travel distance risk was introduced for those drivers who still prefer to choose their routes based on distance rather than travel time. The travel distance can be estimated as a risk as:

$$\textit{Travel Distance Risk} = \textit{Travel Distance} \times \textit{Travel Distance Response Factor} \times \textit{Exposed Population} \quad (4)$$

The *Travel Distance Response Factor* and *Exposed Population* are assumed to be the same as described in the travel time risk. Travel distance can be calculated using:

$$d_{route} = \sum_a L_a \quad (5)$$

where d_{route} is the sum of all travel distances along a path and L_a is the length of link a.

3.1.3. Travel Cost Risk

When deciding on their route, many drivers consider the trip costs that they may incur, which are decided by factors such as travel distance, travel time, fuel cost, tolls, parking cost, and other out-of-pocket costs. The cost to make a trip could be viewed as a risk and assessed as:

$$\textit{Travel Cost Risk} = \textit{Travel Cost} \times \textit{Cost Response Factor} \times \textit{Exposed Population} \tag{6}$$

where the Travel Cost in this case is based on the sum of Fuel Consumption Cost and Tolls, as described in Equation (7); the *Cost Response Factor* and *Exposed Population* are the same as mentioned in travel time and distances risks and are assumed to be the same regardless of route selection and as such they are discounted from consideration by making their values equal to one. Therefore, the comparison between routes is based on travel cost only.

$$\textit{Travel Cost} = \textit{Travel Distance} \times \textit{Fuel Consumption Rate} \times \textit{Fuel Cost} + \textit{Tolls} \tag{7}$$

where the *Travel Distance* is the distance travelled in miles; *Fuel Consumption Rate* in grams per mile calculated using: $39.705188 + \left({}^{702.856}/_{v}\right) + (0.0096227 \times v^2)$, where v is the average vehicle speed in mile per hour (Patil et al., [19]); and *Fuel Cost* in currency value per gram. The *Tolls* apply for some roadway links where tolls are collected. In this study, a constant toll value was assumed for such links.

3.1.4. Accident (Safety) Risk

Traffic safety is of major social and economic concerns to drivers and the public. Roadway traffic accidents phenomena is also a major concern to decision makers struggling to minimize negative impacts on road users. Therefore, improving road safety remains a top priority to transportation authorities to minimize the risk to humans. The accident risk is calculated as:

$$\textit{Accident Risk} = \{\textit{Crash Frequency} \times \textit{Crash Severity}\} \times \textit{Exposed Population} \tag{8}$$

where the *Risk Agent Dose is equal to Crash Frequency*; the *Crash Severity* is considered as the *Response Factor* where the injury impact on exposed population differs based on multiple factors such as road user characteristics (e.g. age, gender, etc.) besides the road factors; and for simplicity, the response factor is assumed to be the same regardless of any route selected; and as such it is discounted from consideration by making their values equal to one. The *Exposed Population* is the number of road users (i.e. vehicle occupants and pedestrians), which can be estimated from traffic volume of each roadway link in the study area.

The crash frequency can be estimated from crash data if readily available; otherwise crash frequency can be predicted using the AASHTO's Highway Safety Manual (HSM) [20] where it is the case in this study. The HSM's model for estimating the crash frequencies is shown in Equation (9):

$$N_{\text{predicted}} = \left\{N_{\text{spf,a}} \times (\text{CMF}_{1a} \times \text{CMF}_{2a} \cdots \times \text{CMF}_{va})\right\} \times C_x \tag{9}$$

where $N_{\text{predicted}}$ is the predicted average crash frequency per year on link a. $N_{\text{spf,a}}$ is the predicted average crash frequency determined for base conditions of the Safety Performance Functions

(SPFs) developed for link a. CMF_{ya} is accident modification factor specific to link a and specific geometric design and traffic control feature y. C_x is a calibration factor to adjust SPF for local conditions for link a.

3.1.5. Air Emissions Risk

As a contribution to green routing, the proposed methodology considers risk due to vehicle air emissions, such as carbon monoxide (CO), particulate matter (PM), volatile organic carbon (VOC), and nitrogen oxides (NOx). These air pollutants are widely studied by researchers in the field of vehicle air emissions. The risk from emissions can be estimated as follows:

Risk due to Air Emission = Emission Concentration × Emission Response Factor×Exposed Population (10)

where *Emission Concentration (C)* is the risk agent force, which can be estimated for a specific air pollutant using Equation (11) (Luhar and Patil, [21]); the *Emission Response Factor* is the risk factor associated with the specific air pollutant and is considered the same for all travel links and as such it is assigned a value of one; and the *Exposed Population* is the population surrounding the road within a fixed impact zone and includes the road users within the road link. Therefore, the *Risk due to Air Emissions* is dependent on the *Emission Concentration* and the *Exposed Population* that vary from one link to another. The risks due to different emissions can be added together to estimate risk from all concerned air pollutants.

$$\mathrm{C} = \frac{\mathrm{Q}}{2\sqrt{2\pi}\sigma_z \mathrm{U}\sin\theta} * [\exp\frac{-(\mathrm{z}-\mathrm{H})^2}{2\sigma_z^2} + \exp\frac{-(\mathrm{z}+\mathrm{H})^2}{2\sigma_z^2}]*[\mathrm{erf}\frac{\sin\theta\left(\frac{\mathrm{L}}{2}-\mathrm{y}\right)-\mathrm{x}\cos\theta}{2\sigma_y} + \mathrm{erf}\frac{\sin\theta\left(\frac{\mathrm{L}}{2}+\mathrm{y}\right)+\mathrm{x}\cos\theta}{2\sigma_y}] \tag{11}$$

where C is the emission concentration in g/m^3; Q is the emission rate in gram per second-meter, U is the wind speed (meter/second), σ_y and σ_z are dispersion coefficients (meter), H is the plume height (meter), L is the length of line source (meter), θ is the angle between wind and roadway, x and y are the distances from center of line air emissions source (meter), z is the elevation from line source (meter).

Emission Rate (Q) expressions are available for a variety of emitted air pollutants. For example, the following emission rate expression for CO_2 (Patil et al., [19]): $Q/V_a=129.533 + (^{2217.694}/_{v}) + (0.027771 \times v^2)$ where Q is the emission rate in g/veh-km, v is the average speed; and V_a is traffic volume on road link a (veh/hr).

3.1.6. Noise Risk

Another environment-related risk considered in this study is noise emission risk. Like the air emission risk, the noise emission risk is estimated using as:

Risk from Noise = Noise Level × Noise Response Factor × Exposed Population (14)

The Noise Level could be estimated from any appropriate noise model, such as the Ontario Ministry of Transport noise prediction model used in this study, as shown in Equation (15):

$$L_{eq} = 42.3 + 10.2\ log(V_c + 6\ V_T) - 13.9\ log(D) + 0.1\ S \tag{15}$$

where L_{eq} is the equivalent sound level for one hour (dB); V_c is the volume of light vehicles (veh/hr); V_T is the volume of trucks (veh/hr); D is the distance from edge of pavement to receiver (meter) which was assumed to be 7 meters; and *S* is the average speed of traffic for one hour (km/hr) which was replaced in our case by the posted speed limit on the road due to the lack of average vehicle speed data. Other models to estimate noise levels can be certainly used, if available.

The *Noise Response Factor* is related to annoyance, which can be estimated from the *Noise Level* using a model such as the one in Equation (16) (Patil et al., [19]). Assessment of risk from noise on any travel link requires: estimating the noise level, conversion of noise level into a measure of annoyance (A_{link}), and estimating the exposed population within a specific buffer from the edge of the pavement (a value of 7 meters was used in this study):

$$A_{link} = 1.795 \times 10^{-4}\left(L_{eq} - 37\right)^3 + 2.110 \times 10^{-2}\left(L_{eq} - 37\right)^2 + 0.5353\left(L_{eq} - 37\right) \tag{16}$$

3.2. Integrating the various risks using AHP

Once the various risks are estimated for each link of the roadway network, the next step is to integrate these risks into a single measure to be used for determining the optimal (i.e., the least risky) route. Given that these risks vary in terms of their relative importance to different stakeholders, the Analytical Hierarchy Process (AHP) is utilized to rank these risks through assigning different weights. The AHP is a widely-used technique for analysing difficult decisions that depend on experts' points of view of the importance of competing objectives. AHP was developed by Saaty in the 1970s where it was refined and developed since then. In this study, we followed a methodology of ranking based on a study by Barilla et al. [22], which also used AHP to combine a set of defined objectives in a comprehensive risk-based routing analysis.

While the AHP is employed to determine the relative importance weight of each risk over the other, the methodology is flexible to allow the user to rank the risks depending on his/her own point of view of the importance of these risks so that the optimal route can be calculated based on the user's interest. The authors believe that in societies where a great level of awareness of sustainable transportation exists, many users will place higher weights on environmental and social risks when making their routing decisions.

The assignment of weights starts with a pair-wise comparison of the importance of the different risks using a scale such as that shown in Table 1. Based on pair-wise comparisons of the various risks (i.e., *m* types of risks), Barilla et al. [22] organized the weights in a response matrix [P] of dimension (*m* x *m*), whose elements represent the relative importance of the different risks. The elements of matrix [P] also represent the relative weights of risks, as shown in Equation (17). To estimate the weights of the different risks, Barrilla et al. [22] suggested that it is sufficient to find the maximum eigenvalue, λ_{max} of matrix [P] which satisfies the following relationship between [P] and the transpose of the weights matrix, W = [w_1 w_2, …, w_m] (Equation 18).

$$P = \begin{bmatrix} w_1/w_1 & \cdots & w_1/w_m \\ \vdots & \ddots & \vdots \\ w_m/w_1 & \cdots & w_m/w_m \end{bmatrix} \tag{17}$$

$$[P] \times \bar{W} = \lambda_{max} \times \bar{W} \tag{18}$$

The various weights can be estimated using a questionnaire to infer how various users weigh the various risks. In the questionnaire, each user is basically asked to compare one risk over another for each possible couple of risks considered and to assign a score for its importance as per Table 1.

Tab. 1 - Scoring scale used for the pair-wise comparison (Barilla et al., [22])

Score Value	Definition
1	Equal Importance
3	Three Times Important
5	Five Times Important
7	Seven Times Important
9	Nine Times Important
2, 4, 6, 8	Intermediate values between the two adjacent

Responses received from the users are then used to determine the weight matrix [W], which will provide the weights to combine the different risks into a single comprehensive measure as shown in Equation (19) (Barilla et al., [22]):

$$v(k) = \sum_{i=1}^{n}(r_i(k))^{-w_i} \tag{19}$$

where *v(k)* is the combined risk; r_i is the normalized risk type *i*; and w_i is the weight assigned to risk type *i*.

It is worth mentioning that because the utilized risk categories have different units, the integration method described above is based on normalization of the various factors to allow such integration. Normalization of any risk category, as described by Barilla et al. [22], is achieved through dividing the individual risk value for each route over the sum of all the risk values of all roadway network.

Therefore, the output of normalization are dimensionless risk values that range between 0 to 1 for the routes involved. The weights of the different risk categories are then used to integrate the various risks into one comprehensive value.

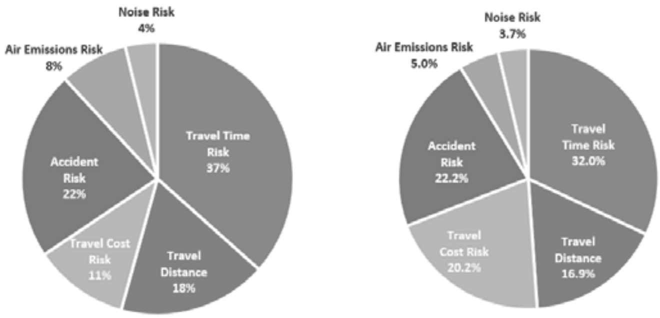
3.3. Finding the least-risky route

After the various risks are integrated into a single comprehensive measure for each roadway link, a shortest path algorithm, such as Dijkstra's, is used to find the least-risky route between any origin and destination pair defined by the user. It is worth mentioning that the methodology is implemented in a GIS environment, which allows implementation of the shortest-path algorithm and displaying the final results as maps. The next section demonstrates the applicability of the proposed methodology to Sharjah City, UAE as a case study.

4. Results and discussion

The previous section outlined a framework for risk-based routing that considers and integrates multiple constraints. The methodology was applied to a real-world setting, namely Sharjah City, which is the third largest city in the United Arab Emirates. It is worth mentioning that a comprehensive GIS database of the main roadway network in the City was not available and therefore was developed for purposes of the study. The database contained all relevant traffic and physical features of the major road links. Because such a database did not exist before, substantial effort was spent on collecting relevant information and developing the database.

To assign weights to the different risk categories according to the AHP pair-wise comparison method, a questionnaire was prepared and distributed to over 100 randomly selected users from two different groups: general public (65.4% of total respondents) and experts (34.6% of total respondents) involved in transportation issues, including planners, academics, decision makers, and transportation/environmental professionals.



(a) Weights using public opinion (b) Weights using expert opinion

Fig. 2 - Importance weights using AHP: (a) Public opinions and (b) Expert opinions

The authors utilized an online survey and personal interviews. The responses of both groups were then used to deduce the weights used to combine the various risks into a single measure. Figure 2 (a) and (b) show the weights assigned by the general public and experts, respectively. As can be seen, the views of the expert and members of the public on the importance of the various risks are close to each other. For example, both groups considered travel time to be of the most important whereas the noise risk to be the least important. However, the public considered the travel distance to be more important than the travel cost, but it was the contrary for the experts. Nevertheless, using either the weights assigned by the experts or the public gave the same optimal route results.

To demonstrate the applicability of the proposed methodology, the least-risky route was found for a popular origin-destination trip (typical student trip from the city's downtown to the university's campus). Figures 3 to 8 show the least-risky route based on each of the risk types considered in this study: travel time (Figure 3), travel distance (Figure 4), travel cost risk (Figure 5), accident risk (Figure 6), air emissions risk (Figure 7), and noise emissions risk (Figure 8). In addition to showing the best routes, these figures also show the variations of the risk, on link-by-link basis, and the cumulative risk along each route.

More importantly, Figure 9 shows the least-risky route using the integrated (or weighted) risk. It is not difficult to notice that this route is highly influenced by travel distance (Figure 4) and travel cost (Figure 5) and reflects travel time (Figure 3) and accident risk (Figure 6).

This is not surprising given that these factors carry most of the weight. The advantages of utilizing GIS to find the least-risky route cannot be emphasized enough in terms of the presentation, ease, and accuracy of the routing routes. To ease the comparison, Figure 10 illustrates these least-risky routes based on each individual risk as well as the total integrated risk.

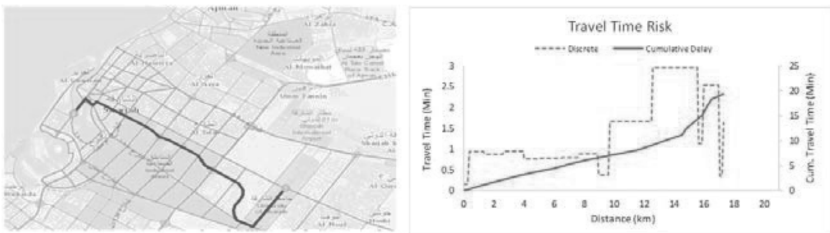


Fig. 3 - Least-risky route based on travel time

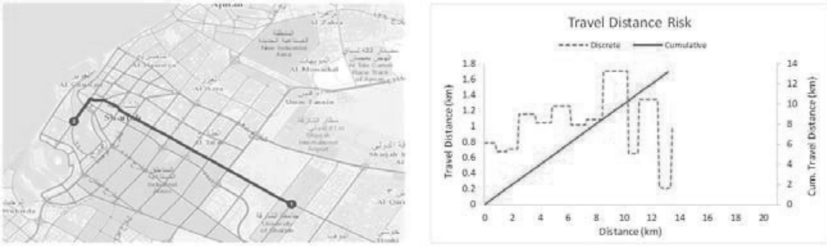


Fig. 4 - Least-risky route based on travel distance

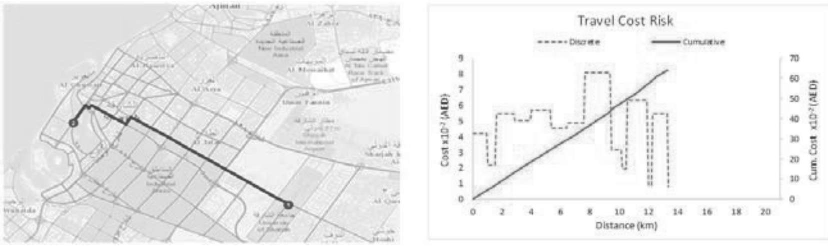


Fig. 5 - Least-risky route based on travel cost

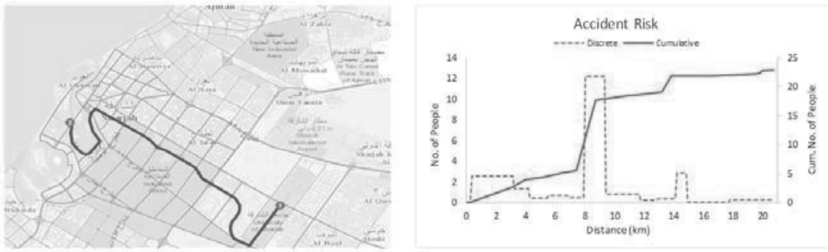


Fig. 6 - Least-risky route based on accident risk

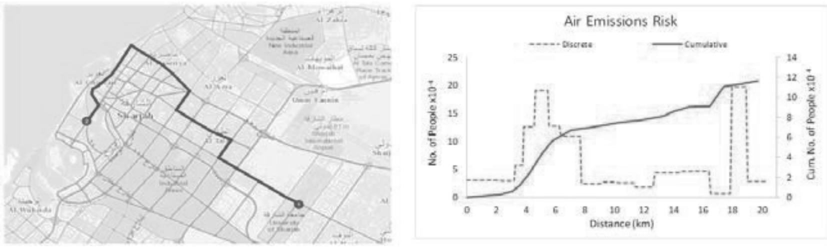


Fig. 7 - Least-risky route based on air emissions risk

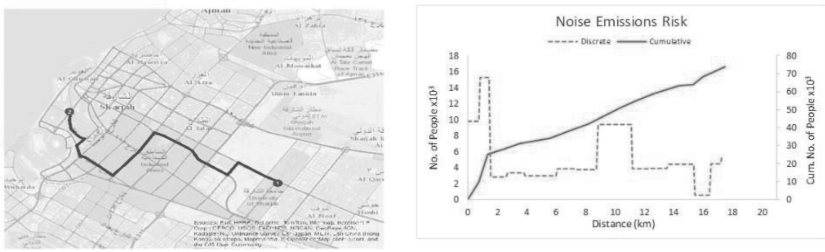


Fig. 8 - Least-risky route based on noise emissions risk

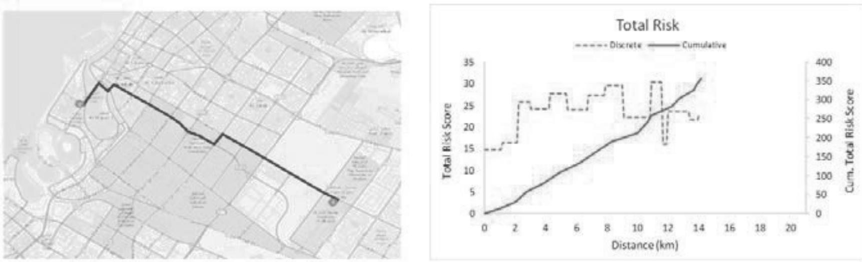


Fig. 9 - Least-risky route based on integrated total risk

To further demonstrate the proposed methodology, it was applied on a set of four pre-determined popular routes to make the same origin-destination trip as before, i.e. downtown to the university campus, as shown in Figure 11. For each of these routes, the six aforementioned risks as well as the integrated total risk were individually estimated. Table 2 summarizes these risk estimates in addition to those for the least-risky route (designated as Route 5) based on the integrated total risk, previously shown in Figure 9. In addition, the table shows the best alternative for each of the considered risks.

To make it easier for the reader to compare the various performance measures among the different routes, Table 2 also shows the percent difference (+ Increase / - Decrease) relative to the least-risky route.

As can be seen in Table 2, the best alternative is the least-risky route followed by Route 3, designated as University City Road. The latter has proved to be the best alternative in two of the six individual risks whereas the least-risky route proved to be the best in another three risks, in addition of-course to be the best in terms of the integrated total risk. One can easily see that Route 3 and the least-risky route (Route 5) follow close paths; nevertheless, the least-risky route has an integrated total risk that is less than Route 3. Overall, the least-risky route has between 7% to 33% less risk compared to other routes.

This result confirms that the proposed framework is able to identify successfully the least-risky route using the proposed integrated total risk as compared to individual performance measures.

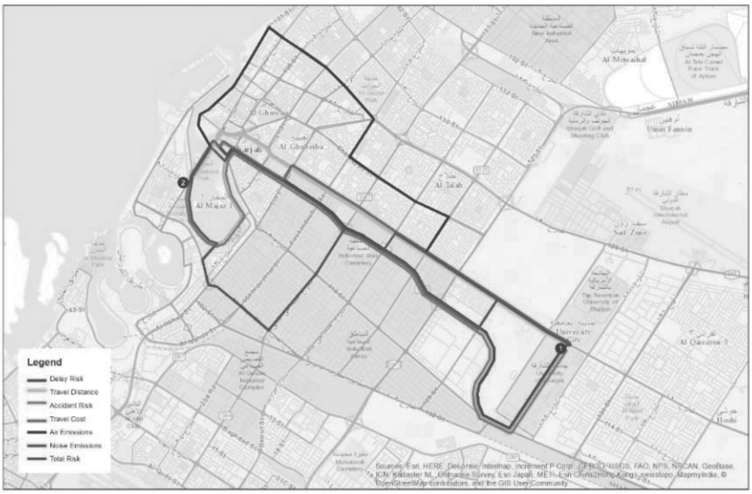


Fig. 10 - Least-risky routes based on individual and integrated total risks