iRouteSafe: Personalized Cloud-Based Route Planning Based on Risk Profiles of Drivers

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***Abstract*—Car accidents are one of the leading causes of human fatalities worldwide. Given the variation in capabilities of drivers in different driving conditions, a personalized safety-based routing - that considers the variation in driving skills - is a step towards minimizing drivers' individual and aggregate risk. In this paper, we propose iRouteSafe, a novel cloud-based route planner that utilizes drivers' individualized risk profiles in suggesting routing options based on drivers' personal skillfulness levels. Using graph theory concepts, the routing problem is formulated as a combinatorial multi-objective optimization problem where the objective is to find the optimal route that minimizes cost function composed of a route's travel time, expected risk, and the personal driver-specific risk in such driving routes. To highlight the significance of the proposed route planning, a case study is presented.**

***Index Terms*—Route planning, driver profiling, driving behavior classification, cloud computing, telematics, intelligent transportation systems (ITS)**

I. Introduction

Despite the recent safety measures that are being adopted by governments and car manufacturers to ensure safe driving, the road traffic death rate is still high. The 2018 global status report on road safety issued by the World Health Organization (WHO) indicated that 1.35 million people across the world are losing their lives every year due to road injuries [1]. Such a significant fatality number has made road injuries the eighth global cause of death in 2016. Moreover, the report dictates that most countries spend approximately 3% of their gross domestic products (GDP) to cover road crash expenses in the form of injury treatment, helping bereaved families, etc. [2]. With these alarming statistics, more innovative proposals are needed to minimize road crash rates.

Considering the effect that driving conditions can have on drivers, providing them with the choice to avoid driving in risky environments could certainly mitigate crash risk. Current navigation systems only provide route suggestions based on travel time or distance, hence, safety-based routing systems that suggest routes based on their expected risk are needed [3]. Safety-based routing terminology comes in different levels of abstraction. A general definition of such terminology is to find the safest route between a source and a destination among several potential routes based on the expected crash risk of each route. A common approach to predict such risk is through analyzing the crash records of roads with similar static (e.g., road alignment, traffic control) and dynamic (e.g., traffic density, weather conditions) environmental attributes. Although this approach covers the safety-based routing notion from a holistic perspective, it ignores the variation in the personal driving skill levels of drivers in the same driving conditions.

With the recent advancements in vehicular sensing technologies and low-cost platforms such as On-Board Diagnostics (OBD) and smartphone sensors, the accurate detection of various driving behaviors and the ability to profile drivers has become affordable [4]. Furthermore, the recent developments in vehicle-to-cloud (V2C), and cloud computing technologies have made it easy to send detected behaviors from vehicles to a cloud and couple the detected behaviors with the real-time environmental context as they occurred [5]. Such coupling paves the road to an environmental-aware driver profiling which measures the individual competence levels of drivers in different driving environments. With this information stored in the cloud, a personalized safety-based route planning that considers the individual risk profile of a driver is now possible.

In this paper, the personalized safety-based route planning is formulated as a multi-objective optimization problem in which the cost function is composed of the travel time of a route, and weighted general and personal expected risks taking such a route. The main contributions of this paper are summarized as follows:

1) A novel personalized safety-based routing framework that is founded on the personal risk profiles of drivers in various driving environments is proposed with the underlying in-vehicle and on-cloud processes.
2) The personalized safety-based routing problem is formulated as a multi-objective optimization problem and a possible solution is provided using a linear programming approach.
3) A real-world case study from the province of Ontario, Canada is presented and discussed to demonstrate the difference between current and proposed routing systems and to highlight the importance of the envisioned framework.

The remainder of this paper is organized as follows. In section

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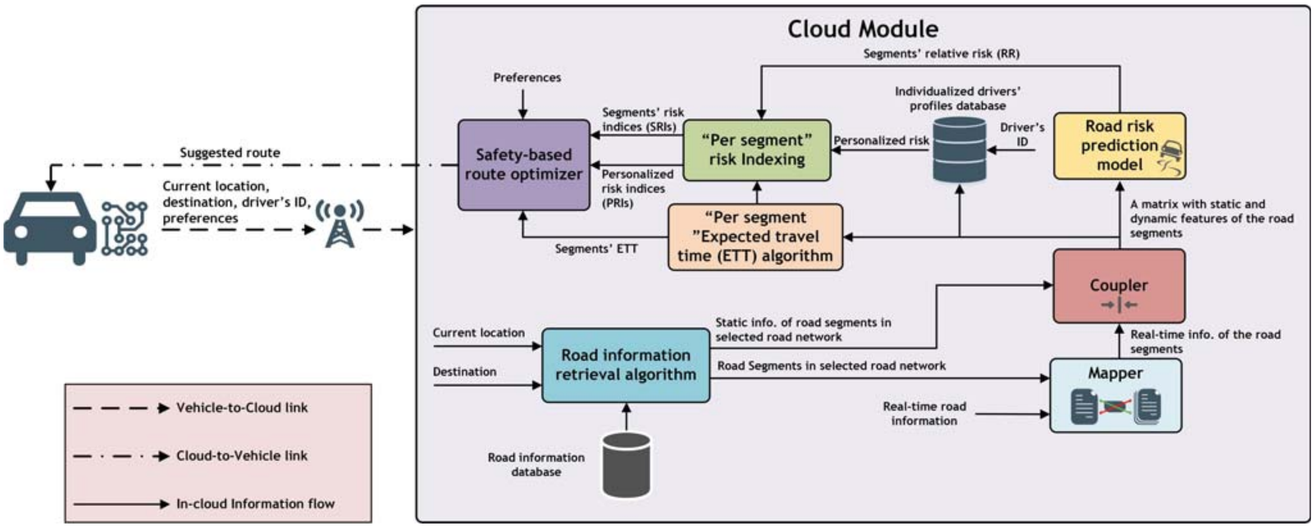

Fig. 1: iRouteSafe: proposed personalized safety-based route planning system.

II, background and related work are presented. Section III discusses the proposed cloud-based routing framework with the underlying sub-systems. In section IV, the route planning optimization problem is formulated and discussed. Section V presents a real-world case study to demonstrate the proposed routing system. The conclusion is given in section VI.

II. Background and Related Work

Current popular route planning systems such as Google Maps primarily rely on the expected travel time in suggesting routes. Vehicle routing based on the estimated travel time problem has been extensively covered in the literature. The main objective in this problem revolves around finding the optimal route that has the minimum overall travel time among a number of potential routes given the static and dynamic attributes of the route [6]. Eco-route planning has been recently studied in the literature. In [7], authors proposed a cloud-based system that provides heavy duty vehicles with optimal routes that minimizes fuel consumption while satisfying a constraint on the maximum travel time. Recently, authors in [8] proposed a fuzzification route recommendation system that suggests a route based on the condition of its segments. Safety-based route planning has also been studied in literature. In [9], the author discussed an envisioned IoT-based framework that is expected to facilitate the employment of safety-based routing. Authors in [10] proposed a risk prediction model that utilizes a large-scale road and crash dataset to predict crash rates in road segments based on eight static road features.

Despite the research efforts mentioned above, to the best of our knowledge a safety-based route planner that takes into account the individual differences in driving competence levels among drivers in different driving environments is still missing. For instance, although curved roads with high traffic density and foggy weather conditions could be risky from a holistic standpoint, drivers may have various risk rates in such an environment depending on their personal competence levels. Using the individual risk profile of a driver in calculating his/her personal overall risk in different routes is presented and thoroughly explained next.

III. iRouteSafe: System Architecture

In this section, we present an overview of the personalized safety-based routing system followed by an explanation of the individual safety-based system's components.

A. *Overview*

Figure 1 depicts the proposed iRouteSafe system's architecture. In the proposed iRouteSafe system, the route planning process is initiated by the subject driver (sd) who communicates his/her current GPS co-ordinates, desired destination, identification number, and desired personalized routing preferences to the cloud through a cellular wireless link. An sd can choose a route based on the minimum expected travel time (ETT), minimum risk (from both personalized and holistic perspectives), or based on the joint inclusion of these preferences in the route's optimization cost function.

In the cloud, the $sd's$ GPS current location (source) and desired destination are inputted to a road information retrieval module which retrieves the potential road segments (R) from source to destination as abstracted directed graph edges, and the segments' corresponding static features (Env_s) from the road information data-base. Then, with an access to the real-time road information, a mapping function f matches the potential road segments with their corresponding real-time information (Env_d) including their weather conditions, traffic density levels, and lighting conditions.

$$f : R \rightarrow Env_d \tag{1}$$

After that, the static and dynamic features of each potential segment are merged together through a coupler in a matrix structure ($Env = [Env_s, Env_d]$) with each row representing the overall features of one potential road segment. Given the

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TABLE I: Features of driving environments

Static features			Dynamic features		
Traffic flow	**Traffic control**	**Alignment**	**Weather**	**Traffic density**	**Lighting**
Divided	No traffic control	Straight	Normal	Free flow	Darkness; lighted
Not-divided	Traffic signal	Curved left	Fog	Flow with some restrictions	Darkness; not lighted
One-way traffic	Traffic sign	Curved right	Mist	Unstable flow	Dawn
No lanes	-	-	Rain and fog	Forced traffic flow conditions	Daylight
-	-	-	Rain	-	Dusk
-	-	-	Sleet	-	-
-	-	-	Snow	-	-
-	-	-	Snow/sleet and fog	-	-

static and dynamic features of potential road segments, a trained supervised risk prediction model predicts the relative risks (RRs) of the segments, where RR is calculated as the relative crash and near-crash risk probability as further explained in section III.B. Moreover, to retrieve the personalized competence levels of the sd for the potential road segments, Env is fed to a database containing updated risk scores of the sd in road segments with similar features to the potential road segments. The personalized risk scores of the sd in the potential road segments are extracted from the personalized driver profile database given the identification number of the sd. Also, Env is utilized to calculate the expected travel times of the road segments ($ETTs$). The information of the general RR, personalized risk scores, and $ETTs$ of potential road segments is then passed to the "per segment risk indexing" module which hosts two utility functions $\mathcal{F}(.)$ and $\mathcal{G}(.)$ that respectively assign two risk indices RI_{gen} and RI_{per} for each road segment corresponding to its general and personalized risks. The calculation of RI_{gen} and RI_{per} is detailed in section III.D. Finally, the segment $ETTs$, general and personalized risk indices are provided to the proposed multi-objective safety-based route optimizer which, based on the $sd's$ preferences, calculates the optimal route and sends it back to the sd.

B. Road risk prediction model

Road risk in the context of this paper refers to the general risk imposed on a driver when exposed to a certain road environment, regardless of the personal driving skills of that driver. By definition, such risk does not vary between drivers as it solely depends on the road's architecture and dynamic features. Road risk is calculated herein in terms of the road's crash and near-crash rates, where near-crash events are the events that require a defensive driving maneuver from the driver to avoid being involved in a crash.

In this paper, SHRP2, a large-scale naturalistic driving study [11], is utilized to develop the road risk prediction model. In SHRP2 event details table, more than 29,000 events are recorded from 3,542 drivers, with each event being linked to the environmental context it occurred in. Events are divided into three main classes: crash, near-crash, and balanced baseline events (i.e., normal driving episodes randomly captured for each driver and their number per driver depends on the total amount of his/her total driving time). Using the environmental context during such events as risk predictors, the risk prediction is defined as the process:

$$\mathcal{F} : Env_i \rightarrow RR(Env_i) \tag{2}$$

where $RR(Env_i)$ is defined as the relative risk of Env_i in SHRP2 dataset and is mathematically expressed as:

$$RR(Env_i) = \frac{P(Risk|Env_i)}{P(Risk|Env_i^{'})} \tag{3}$$

where $P(Risk|Env_i)$ is the risk probability given the exposure to driving environment i, and $P(Risk|Env_i^{'})$ is the risk probability in all other environments except i. Risk probability in a certain driving environment is calculated in terms of the number of crash, near-crash, and baseline events as:

$$P(Risk|Env_i) = \frac{C_i + NC_i}{B_i + C_i + NC_i} \tag{4}$$

where C_i, NC_i, and B_i are respectively the number of crash, near-crash, and baseline events captured in driving environment i. Since $P(Risk|Env_i)$ depends on the sampling rate at which the baseline events are taken, the relative risk probability rather than risk probability has been adopted as a risk measure.

In this work, a random forest (RF) regressor with 100 decision trees and MSE splitting criterion is trained using SHRP2 data samples to reflect the relative risk of different driving environments. Table I depicts the considered environmental road features.

C. Individualized drivers' profiles database

Driver profiling is a dynamic personalized process that targets the detection of a driver's competencies based on his/her driving behaviors. Driver profiling is composed of behavior detection and scoring sub-processes [12]. Figure 2 depicts a summary of the driver profiling process which starts by communicating a detected behavior, $sd's$ current location and identification number to the cloud. Behavior detection is usually performed inside the vehicle by utilizing the in-vehicle sensors such as smart-phone sensors (e.g., accelerometers,

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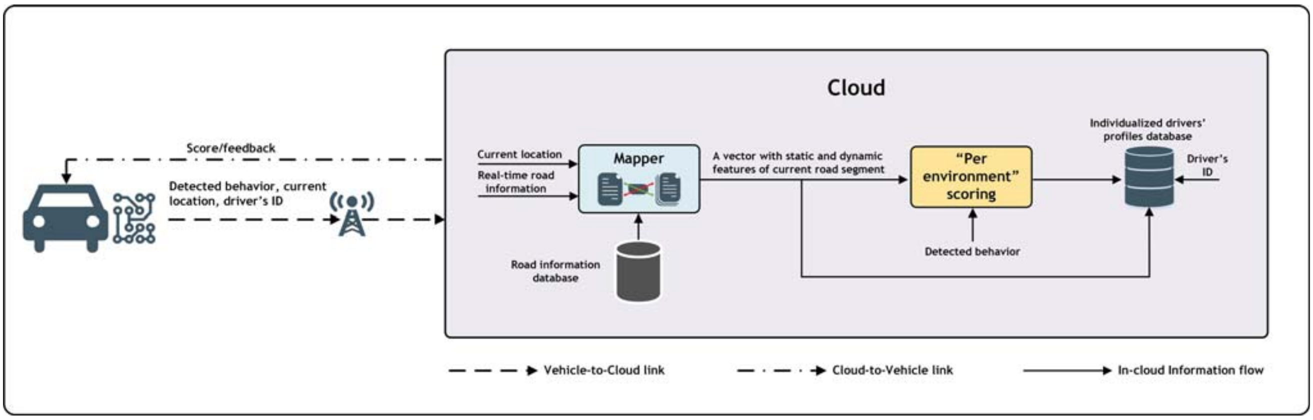

Fig. 2: Driver profiling update after each driving trip.

gyroscopes, GPS) or OBD units. Using such data, behaviors are categorized using a multi-class classifier.

In the cloud, static and real-time features of the road segment where the behavior is detected are extracted and fed to the "per environment" scoring module. This module hosts a trained risk prediction model which predicts risk based on the joint effect of the detected behavior and its environmental context. The scoring module also hosts a feedback sub-module which compares the relative risk of detected behavior to an ad-hoc threshold. A warning is issued to the sd during a driving trip if the relative risk of the detected behavior is high. Based on the average relative risk of different detected behaviors and the $sd's$ compliance to warnings, the $sd's$ "per environment" profile is updated by the end of each trip. The risk score (RS) of sd in a driving environment Env_i is expressed mathematically as:

$$RS_{sd}(Env_i) = \max\left(RR_{sd}(Env_i) - \beta.C_{sd}(Env_i), 0\right) \quad (5)$$

where $RR_{sd}(Env_i)$ and $C_{sd}(Env_i)$ are respectively the average relative risk and compliance of driver sd in driving environment Env_i, and β is a weighting factor the system administrator chooses to specify the importance of $C_{sd}(Env_i)$ in the calculation of $RS_{sd}(Env_i)$ [5].

D. Per segment risk indexing

Two risk indices, SRI and PRI, are assigned to a road segment r based on the RR of the segment and the $sd's$ personal RS in that segment, respectively. SRI is assigned based on two factors. The first is the ETT of the segment which reflects how much time the sd will be exposed to the risk imposed by r, while the second is the RR value of the segment as expressed in equation 6.

$$SRI(r) = \mathcal{F}(ETT(r), RR(r)) \quad (6)$$

Since the risk of the segment has a positive relationship between its ETT and RR values, the SRI utility function can in the form:

$$SRI(r) = (ETT(r) \times RR(r))^{n_1} \quad (7)$$

$ETT(r)$ can be viewed as a factor that weighs the risk of the segment based on the $sd's$ exposure to that risk. n_1 is an integer chosen by the system administrator that determines the effect of the risk of individual route segments on the choice of the overall optimal route. For instance, considering two potential routes $R1$ and $R2$. $R1$ may have a smaller sum of weighted relative risks compared to $R2$ but still be avoided if n_1 is large in case that $R1$ contains a segment or more with very high weighted relative risk.

Similarly, PRI is assigned based on the ETT of a segment and the $sd's$ personal risk score RS in that segment (or in another segment with similar environmental features). The truthfulness (TR) of the RS score is another weighting factor that is utilized to calculate PRI. TR value depends herein on the total exposure time of the sd driver in a driving environment similar to the segment's environment. $TR \in [0, 1]$, with a value of 1 indicating full truthfulness. The mathematical expression of the personal risk index PRI is shown in equation 8.

$$PRI_{sd}(r) = (ETT(r) \times TR_{sd}(r) \times RS_{sd}(r))^{n_2} \quad (8)$$

IV. Personalized Safety-Based Routing

In this section, the proposed route planning problem is formulated using graph theory and linear programming (LP). Planning a route between a source and destination in a road network can be modelled as a digraph where nodes in the graph resemble road network intersections while edges represent road segments.

A digraph is formally represented by the tuple G, where $G = (\mathcal{N}, \mathcal{E})$. $\mathcal{N}$ and $\mathcal{E}$ are respectively representing the set of all nodes in the graph, and the set of all edges (i.e., ordered pairs of nodes) in the graph.

In our proposed route planning problem, each edge ε_{n_i,n_j}, where $\varepsilon_{n_i,n_j} \in \mathcal{E}$, is uniquely characterized by the 3-tuple $(t_{\varepsilon_{n_i,n_j}}, SRI(\varepsilon_{n_i,n_j}), PRI_{sd}(\varepsilon_{n_i,n_j}))$, where $n_i, n_j \in \mathcal{N}$ are any two consecutive nodes in the graph with a direct path, t_{n_i,n_j} is the expected travel time between n_i and n_j, $SRI(\varepsilon_{n_i,n_j})$ is the segment risk index of ε_{n_i,n_j}, and $PRI_{sd}(\varepsilon_{n_i,n_j})$ is the personalized risk index of sd in ε_{n_i,n_j}.

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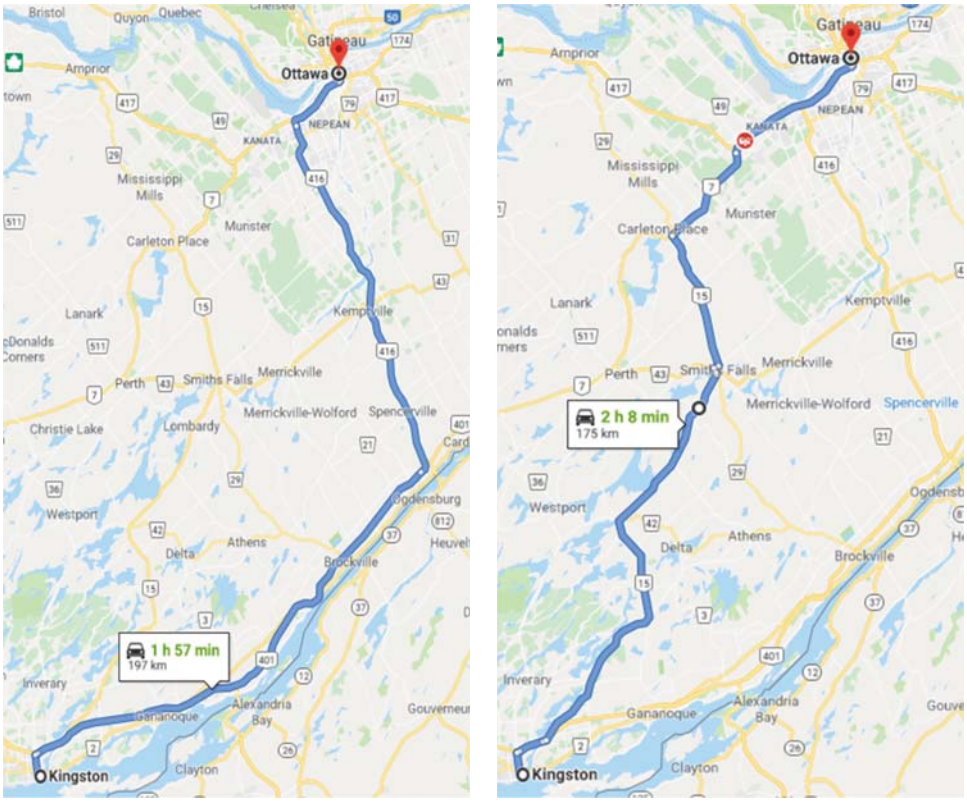

(a) Optimal route according to Google Maps.

(b) Optimal route according to iRouteSafe.

Fig. 3: Route planning case study in Ontario, Canada.

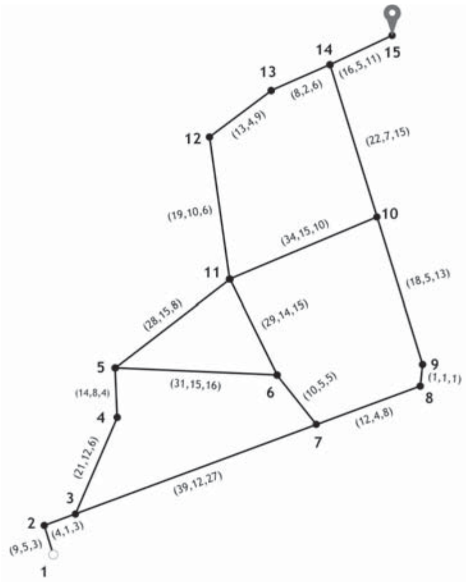

Fig. 4: Road network as a graph.

A path from source to destination in the digraph is a sequence of edges (road segments in our problem) starting from source and ending to destination. Let P denote a matrix containing all paths, where P_l is a vector of nodes that form a possible path in P. The personalized safety-based routing problem is formulated as a combinatorial multi-objective optimization problem as shown in equation 9:

$$\min_{l} \sum_{i=0,j=i+1}^{i=M-1,j=M} t_{\varepsilon_{P_l(i),P_l(j)}} + \gamma_1.SRI(\varepsilon_{P_l(i),P_l(j)}) + \gamma_2.PRI_{sd}(\varepsilon_{P_l(i),P_l(j)}) \tag{9}$$

where $P_l(i)$ is the node that corresponds to the i_{th} index of P_l, M is the last node in path P_l which is the destination node, γ_1 and γ_2 are weighting factors which reflect how much importance is given to the safety terms. So the problem is to find the integer l which corresponds to the optimal path P_l.

The problem is further formulated as a linear integer programming (LIP) problem. Lets define the binary variable x_{n_i,n_j} as follows:

$$x_{n_i,n_j} = \begin{cases} 1, & \text{if } \varepsilon_{n_i,n_j} \text{is a segment in the optimal path} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

And let $C(\varepsilon_{n_i,n_j})$ be the cost of travelling in edge ε_{n_i,n_j} which is expressed as:

$$C(\varepsilon_{n_i,n_j}) = t_{\varepsilon_{n_i,n_j}} + \gamma_1.SRI(\varepsilon_{n_i,n_j}) + \gamma_2.PRI_{sd}(\varepsilon_{n_i,n_j}) \tag{11}$$

So the LIP problem can be formulated as:

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$$\text{Minimize} \quad \sum_{\forall \varepsilon_{n_i,n_j} \in \mathcal{E}} C(\varepsilon_{n_i,n_j}).x_{n_i,n_j} \tag{12}$$

$$\text{subject to} \quad \sum_{\forall \varepsilon_{n_0,n_k} \in \mathcal{E}} x_{n_0,n_k} = 1 \tag{13}$$

$$\sum_{\forall \varepsilon_{n_i,n_j} \in \mathcal{E}} x_{n_i,n_j} - \sum_{\forall \varepsilon_{n_j,n_m} \in \mathcal{E}} x_{n_j,n_m} = 0 \tag{14}$$

$$\sum_{\forall \varepsilon_{n_k,n_M} \in \mathcal{E}} x_{n_k,n_M} = 1 \tag{15}$$

$$\sum_{\forall \varepsilon_{n_i,n_j} \in \mathcal{E}} \gamma_1.SRI(\varepsilon_{n_i,n_j}) + \gamma_2.PRI_{sd}(\varepsilon_{n_i,n_j}) < s_{th} \tag{16}$$

where the constraints in equations 13 and 15 are necessary to ensure that there is only one arc leaving the source node and only one arc arriving to the destination node, respectively. The constraint in equation 14 is important to ensure the path continuity where n_j is any intermediate node in the graph (i.e., $n_j \neq n_0$ and $n_j \neq n_M$). The constraint in equation 16 defines a user-specific safety constraint for which a route is avoided if its total risk is above s_{th}.

V. Case Study

In this section, a route planning case study which highlights the effectiveness of the proposed route planning scheme is discussed. The case study is from the province of Ontario in Canada where the requested route is from the city of Kingston to Ottawa. The trip request was performed on Sunday, June 2nd at 10:15 PM EDT. Figure 3a depicts the proposed Google Maps route. Considering the real-time traffic and road conditions, the selected Google Maps route resulted in the minimum expected travel time. Figure 4 shows the extracted graph that represents the road network. In this figure, the 3-tuple presented on each road segment represents the expected travel time of the segment, general risk index, and personalized risk index, respectively. General and personalized risk indices were generated using equations 7 and 8 considering both the static and real-time environmental features shown in table I. The nodes in this figure resemble the major road intersections. To choose the optimal route which jointly considers the travel time and risk, we used Gurobi optimizer to solve the optimization problem in equations 12 through 15. The optimization parameters that are used in this case study are presented in table II. In table II, the values of γ_1 ad γ_2 shows that more weight was given to the personalized risk index of the subject driver than the general segment risk index. Also road segments in this case study are linearly penalized for their SRI and PRI values as indicted from n_1 and n_2 values. The optimal iRoutesafe route follows Figure 4 node sequence 1-2-3-4-5-11-12-13-14-15 and is depicted in Figure 3b.

TABLE II: Optimization parameters of the case study

Optimization Parameter	Value
γ_1	1
γ_2	2
n_1	1
n_2	1
TR	$\overrightarrow{1}$
s_{th}	210

VI. Conclusion

In this paper, a novel cloud-based route planning framework was presented. In the proposed framework, the system selects the route which jointly minimizes the expected travel time and the risk from a holistic and personalized perspectives. Using static and dynamic environmental attributes, a customized regressor was trained to reflect the expected relative risk of road segments. The novelty in the proposed framework appears in the incorporation of the personalized drivers' risk profiles in the calculation of the overall route risk. Taking to account such variation in drivers' skillfulness levels in the same driving environment is certainly crucial to minimize the aggregate risk. Using graph theory and linear programming, the problem was formulated as an integer linear programming (LIP) problem. To highlight the effectiveness of the proposed system, Gurobi optimizer was utilized to solve a real route planning problem from the province of Ontario in Canada.

References

[1] "WHO | Global status report on road safety 2018." [Online]. Available: http://www.who.int/violence_injury_prevention/road_safety_status/2018/en/

[2] "Road traffic injuries." [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

[3] A. Taha and N. AbuAli, "Route Planning Considerations for Autonomous Vehicles," *IEEE Communications Magazine*, vol. 56, no. 10, pp. 78–84, Oct. 2018.

[4] G. Castignani, T. Derrmann, R. Frank, and T. Engel, "Driver Behavior Profiling Using Smartphones: A Low-Cost Platform for Driver Monitoring," *IEEE Intelligent Transportation Systems Magazine*, vol. 7, no. 1, pp. 91–102, 2015.

[5] A. Abdelrahman, H. S. Hassanein, and N. Abu-Ali, "A Cloud-Based Environmental-Aware Driver ProfilingFramework Using EnsembleLearning," in *ICC 2019 - 2019 IEEE International Conference on Communications*, May 2019, pp. 1–6.

[6] A. Haghani and S. Jung, "A dynamic vehicle routing problem with time-dependent travel times," *Computers & Operations Research*, vol. 32, no. 11, pp. 2959–2986, Nov. 2005.

[7] G. Difilippo, M. P. Fanti, G. Fiume, A. M. Mangini, and N. Monsel, "A Cloud Optimizer for Eco Route Planning of Heavy Duty Vehicles," in *2018 IEEE Conference on Decision and Control (CDC)*, Dec. 2018, pp. 7142–7147.

[8] A. S. El-Wakeel, A. Noureldin, H. S. Hassanein, and N. Zorba, "iDriveSense: Dynamic Route Planning Involving Roads Quality Information," in *2018 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2018, pp. 1–6.

[9] A. M. Taha, "Facilitating safe vehicle routing in smart cities," in *2017 IEEE International Conference on Communications (ICC)*, May 2017, pp. 1–5.

[10] Z. Li, I. Kolmanovsky, E. Atkins, J. Lu, D. P. Filev, and J. Michelini, "Road Risk Modeling and Cloud-Aided Safety-Based Route Planning," *IEEE Transactions on Cybernetics*, vol. 46, no. 11, pp. 2473–2483, Nov. 2016.

[11] J. M. Hankey, M. A. Perez, and J. A. McClafferty, "Description of the SHRP 2 Naturalistic Database and the Crash, Near-Crash, and Baseline Data Sets," Apr. 2016. [Online]. Available: https://vtechworks.lib.vt.edu/handle/10919/70850

[12] A. Abdelrahman, H. S. Hassanein, and N. Abu-Ali, "Data-driven Robust Scoring Approach for Driver Profiling Applications," in *2018 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2018, pp. 1–6.

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