Multi-Factor Risk Assessment and Route Optimization for Safe Human Travel

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***Abstract*—In the modern world, frequent travel has become a necessity, with vehicles being the primary mode of transportation. Ensuring human safety while traveling is paramount. To address this, it is essential to adopt a combination of numerous static and dynamic parameters to achieve optimal route design in today's complex transportation systems. This study introduces a methodology titled 'Multi-Factor Risk Assessment and Route Optimization for Safe Human Travel', which consists of three stages: Route Optimization, Risk Factor Analysis, and Data Collection. To assess the safety of various routes, a combination of dynamic and static factors is considered. These include traffic, weather, and road conditions, as well as vehicle-related factors such as type, age, and the surrounding road environment. By analyzing simulated data, the technique identifies potential risks and optimizes travel paths accordingly. For segmented routes, risk factors are calculated using both static and dynamic parameters, ensuring a comprehensive safety assessment. Prioritizing user safety, the system dynamically adjusts routes to offer the most cost-effective and safest travel options. This study lays a robust foundation for intelligent transportation systems, aimed at ensuring safer travel for users across a range of scenarios.**

Keywords—Multi-factor risk assessment; route optimization; human travel safety; static and dynamic parameters; risk factor analysis

I. Introduction

Travel safety is a key issue in transportation, particularly as the number of vehicles and the complexity of urban environments increase. The focus in traditional route planning is on reducing travel time or distance, but it frequently ignores important safety considerations, leaving travelers exposed to dangers like accidents, injuries, and crime [1]. These shortcomings highlight the necessity for more holistic methods that place safety on par with efficiency when optimizing routes [2].

This paper addresses these challenges by presenting a novel approach that integrates multiple safety parameters for risk assessment in route optimization. As urbanization and population growth continue, the need for safe, reliable transportation systems is increasingly critical. Recent advancements in risk assessment and route optimization, particularly in dynamic road conditions, are essential for improving the safety of drivers and pedestrians alike [3].

The motivation for this study arises from the pressing need to address the limitations of traditional navigation systems, which often neglect crucial safety factors. The proposed approach leverages a combination of static and dynamic parameters to offer a more comprehensive and adaptive framework for route optimization. By incorporating factors such as traffic density, weather conditions, road environments, and vehicle attributes, the system ensures a holistic evaluation of travel risks. This methodology aims to enhance traveler safety by reducing the likelihood of accidents, fostering user confidence, and supporting the development of intelligent transportation systems.

The primary contribution of this study is the development of a multi-factor risk assessment and route optimization model that dynamically evaluates routes based on safety and efficiency. By tailoring recommendations to different demographics, transportation modes, and real-time conditions, this approach ensures inclusivity and adaptability in route planning. Furthermore, the integration of real-time data enhances the system's ability to adjust dynamically to changing conditions, paving the way for safer and more intelligent transportation networks.

This approach moves beyond conventional navigation by incorporating real-time data and multi-factor analysis to prioritize safety and reduce hazards. Traditional systems that focus primarily on travel time and distance have often overlooked important factors influencing safety and fail to account for the ever-changing road environments and the varying needs of travelers. Multi-Factor risk assessment models now address a broad range of considerations, including time of travel, traffic density, vehicle types, demographics, road conditions, lighting, and traffic patterns [4]. This complete approach optimizes routes not only for efficiency but also for the specific safety needs of different individuals and communities, improving overall travel safety.

Multi-Factor models recognize that higher traffic density, particularly during peak hours, can enhance safety by providing more visibility and reducing risks such as theft or harassment [5]. By incorporating time-sensitive routing that considers traffic density, users can opt for routes that may take longer but offer greater safety.

Optimal routes vary significantly for pedestrians, cyclists, motorcyclists, and those using private or rented vehicles. By tailoring recommendations based on the mode of transport, the system ensures that each user's safety is prioritized.

Demographics and traveler population also play a crucial role in multi- Factor risk assessment. Routes are adapted to reflect the age, gender, and travel patterns of users, fostering safer travel for all.

The use of real-time data enables systems to adjust routes based on current weather, road maintenance, and the availability of lighting, offering a dynamic and comprehensive approach to safer travel. By incorporating these elements into the routing process, multi-Factor models provide a comprehensive approach to safe navigation, addressing the full spectrum of risks that travelers may encounter.

This paper outlines the development and application of multi-factor risk assessment and route optimization models. These models represent a significant advancement in ensuring safer travel for all, paving the way for a future where transportation systems are as safe as they are efficient. The paper is structured as follows: Section II presents the literature review, Section III covers the methodology, Section IV provides the implementation, Section V presents the results and discussion, and Section VI provides the conclusion.

II. Literature Review

Safe human route optimization has emerged as a critical area of research due to the growing need for enhancing road safety, crime activities and minimizing accident risks. A wide range of models and methodologies have been developed, incorporating factors such as road conditions, weather, traffic, and human demographics to provide tailored, safer route options. This literature review explores various strategies and models proposed for optimizing safe travel routes, focusing on both static and dynamic risk factors to ensure safer navigation.

Lingamaneni Indraja et al. [6] examined the correlation between accidents, road conditions, and weather, developing a predictive model using machine learning algorithms like Support Vector Machines and Logistic Regression to identify safe, less accident-prone routes. Yash S. Asawa et al. [7] introduced a User-Specific Safe Route Recommendation System that visually represents safe routes on maps using historical crime data. It operates in two tiers: a Decision Network to capture user-specific features and Geospatial Data Analysis to generate personalized safe routes.

Aruna Pavate et al. [8] developed a system using K-means clustering to categorize routes into security levels, helping women avoid high-crime areas. Isha Puthige et al. [9] devised a danger index based on multiple crime factors at specific locations, using clustering algorithms to identify safe paths. Aliasgar Eranpurwala et al. [10] created the "GoWomaniya" app to help women find safe routes in real-time during moments of distress, leveraging mobile technology.

Deepa Bura et al. [11] developed a model using Google Maps to assess the safety of routes, considering risk factors like security and path quality. Roxan Salehab et al. [12] applied supervised machine learning to predict road sign status in Sweden, contributing to transportation safety by maintaining accurate navigation aids. Deepak Kumar Sharma et al. [13] utilized Random Forest algorithms to predict crash risks based on historical accident data, including weather and road conditions.

Juncai Jiang et al. [14] proposed a framework for assessing urban road collapse risks, using SMOTE and Convolutional Neural Networks to predict road integrity. Mukherjee, D et al. [15] combined historical crash data with proactive pedestrian-vehicular risk assessments to identify and rank high-risk intersections in Kolkata, enhancing pedestrian safety.

Lakshmi et al. [16] conducted a systematic review of Safe Route Guidance Systems, focusing on traffic forecasting, congestion avoidance, and traffic signaling. Llopis-Castelló et al. [17] compared the Highway Safety Manual with geometric design consistency to estimate crash occurrences on road segments in North Carolina.

Al-Bdairi et al. [18] investigated injury severity in weather-related crashes, identifying factors like time of day, driver fatigue, and lack of streetlights that increase accident risks. Qiannan Wang et al. [19] explored how population density impacts autonomous vehicle navigation risks, emphasizing the need for risk-aware path planning. Changhong Zhou et al. [20] developed a road disaster risk assessment model using neural networks and a fuzzy comprehensive evaluation, incorporating environmental and geological factors to predict road disasters.

Nishat Tasnim et al. [21] studied how road geometry, traffic volume, and other features influence accident occurrence. Shan Jiang et al. [22] introduced the Safe Route Mapping (SRM) model, combining crash estimates and conflict risks from driver data to predict route safety. Paul Litzinger et al. [23] proposed an algorithm that incorporates real-time weather forecasts into route planning to enhance safety and efficiency.

Nikhitha Pulmamidi et al. [24] proposed a model for identifying safe routes based on user experience, considering factors like road conditions, weather, and accident frequency. Krishnaraj Pawooskar et al. [25] developed a safety score based on features like hospitals, streetlights, and police stations along routes. Helai Huang et al. [26] emphasized the importance of dynamic traffic conditions and stationary road factors in conflict-based travel route safety assessments. The Road Safety Technical Report [27] highlighted the need for tailored safety solutions based on specific road and traffic conditions.

The reviewed studies demonstrate the importance of integrating diverse factors such as road geometry, weather conditions, and user demographics in optimizing safe routes. Collectively, these efforts contribute to a more complete understanding of route safety optimization, paving the way for smarter, more responsive systems that enhance safety, awareness, and efficiency for all road users.

However, most of these studies focus on single factors or use simplistic models that do not account for the complex interactions between different parameters. This study aims to develop a multi-factor risk assessment model that evaluates the safety of travel routes by considering both static and dynamic factors. The model will use the driven data to classify routes based on their risk levels and identify the safest route between a given source and destination.

III. Methodology

The proposed methodology for "Multi-Factor Risk Assessment and Route Optimization for Safe Human Travel" is designed to address the complexities of modern transportation systems by integrating multiple static and dynamic factors. This approach prioritizes safety, aiming to create a transportation landscape that not only optimizes route efficiency but also enhances the well-being and safety of all users.

The system is divided into three major phases: Data Collection, Risk Factor Analysis, and Route Optimization as shown in Fig. 1. These phases work together find best route based on static and real-time data (dynamic data).

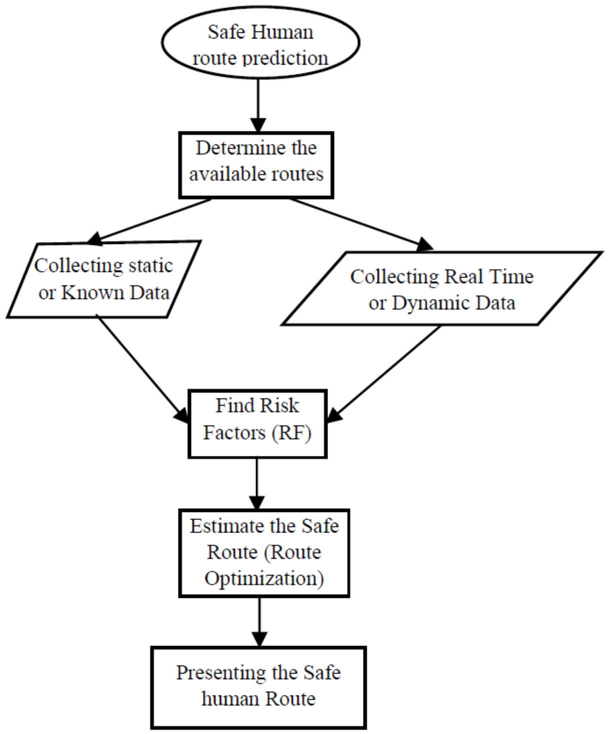

Fig. 1. Phases of route optimization.

A. Data Collection

In the context of Multi-Factor Risk Assessment and Route Optimization for Safe and Efficient Human Travel, the methodology involves a detailed analysis and integration of both static and dynamic parameters as shown in Table I. These parameters are essential for evaluating the safety of various routes and optimizing them to ensure secure travel.

The system accounts for 10 static parameters to ensure route safety. First, the type of vehicle or transport mode is crucial, as different vehicles have distinct requirements for road width, speed limits, and flexibility. Gender-specific concerns are also considered, particularly to avoid areas prone to harassment or crime, especially at certain times of the day. Age is a key factor, influencing mobility and vulnerability; routes safer and more accessible for children, the elderly, and people with mobility challenges are prioritized. For solo travelers, the system suggests safer or more populated routes by factoring in the number of travelers.

TABLE I. LIST OF STATIC AND DYNAMIC PARAMETERS USED

Name of the Parameter	Symbolic Representation
Static Parameters	
Vehicle Type / Transport mode	v
Gender	g
Age	a
Number of Persons travelling	n
Lighting facility	L
Road types	R_t
Public spaces existence	P_s
Road Environment	R_e
Road Complexity	R_x
Availability of CCTV	C
Dynamic Parameters	
Traffic condition	T_c
Weather condition	W_c
Road Conditions	R_c
Time	t

Lighting facilities are critical for night-time safety, so the system prioritizes well-lit routes in the evening and at night. Road type is also considered, as different types offer varying safety levels. Public spaces, such as parks, malls, and police stations, are seen as beneficial, so routes near these areas are preferred. The surrounding environment is evaluated to avoid potentially hazardous zones like forest areas. Road complexity is another factor, with simpler routes being recommended over those with more curves.

Dynamic parameters are also integrated for real-time optimization. Traffic conditions are monitored in real-time to meet the safe condition when mode population density, reducing accident risks and improving travel efficiency. Weather conditions, such as rain, snow, and fog, are tracked, and the system adjusts to avoid dangerous routes during adverse weather. Road conditions, including potholes, construction, and surface quality, are factored in to steer travelers away from hazardous areas. Time of day is another key factor, as poorly lit or high-accident areas are avoided during late hours.

The methodology for multi-factor risk assessment and route optimization begins with data collection. For the data simulation, the available routes between source and destination need to be identified. After the routes are identified, the route may be divided into partitions. A partition refers to a section of the route with a different road type. For example, the entire route section may consist of rural village roads, state highways, or national high ways. Before set the values to static and dynamic parameters, each route is divided into 100-m segments.

The static and dynamic parameter values for each segment are simulated using a randomizer function in Python. To generate random values with the randomizer function, we initialize the static parameter value, such as road type. Based on the road type, the randomizer uses a uniform distribution to set the values for public space existence, road environment, and road complexity for the chosen percentage (minimum and maximum). The dynamic parameters are generated using a normal distribution with the chosen percentage (minimum and maximum) based on the road type and public space existence.

The algorithm for the randomizer function is provided in Algorithm 1:

Algorithm 1: Randomizer Function (generate values)

```
Segment the selected route;
Initialize the road type of each segment;
For all road segments () do
    For parameters (Ps, Re, Rx, C, Tc, Wc, Rc) do
        if parameter_type is "static" then
            Generate a value using a uniform distribution within
            the range [min_value, max_value]
        else if parameter_type is "dynamic" then
            Generate a value using a normal distribution within
            the range [min_value, max_value]
        End
        Return generated value for the parameter
    End
End
```

B. Parameter Value Fixation

We identified 14 key parameters that significantly impact travel safety. Each parameter is symbolically represented and assigned a value between 0 and 1, indicating its influence on the overall risk factor. The value fixations on parameters are given as follows:

1) Vehicle type / transport mode (v): Different types of vehicles have varying levels of stability, speed, and safety features, which influence their risk factor. For example, two-wheelers are generally considered more vulnerable than cars or vans, hence assigned a higher risk value (0.7 for two-wheelers, 0.5 for cars, and 0.3 for vans).

2) Gender (g): Research indicates that gender can impact travel behavior and risk perception. Male travelers are feeling safer and ready to face risk than Female travelers. Hence the value is fixed as 0.9 for female and 0.6 for males. The average gender risk factor is calculated based on the average risk factor of all persons travelling.

3) Age (a): Age influences factors such as reflexes, experience, and risk-facing tendencies. Younger travelers (aged 0-15 years) have a higher risk value (0.9) due to inexperience. Travelers aged 15-30 years are assigned a risk value of 0.5. Those aged 30-45 years are considered the safest, with a lower risk value of 0.2. Travelers aged 46-60 years have a risk value of 0.3, while those over 60 years are considered to have moderate risk, with a value of 0.5. The average age risk factor is calculated based on the number of persons traveling.

4) Number of persons traveling (n): The risk value for traveling decreases as the group size increases, with a risk value of 0.8 for solo travelers, 0.5 for two persons, 0.3 for groups of 3-5, and the lowest risk value of 0.1 for groups larger than five.

5) Lighting facility (L): Adequate lighting reduces the risk of accidents, robberies and other criminal activities. Segments with no artificial lighting are assigned the highest risk value (1), while light-facilitated segments have a value of 0. During the day, the value is set to 0 since there is no need of artificial light. At night, the value is also set to 0 if adequate lighting exists; otherwise, it is set to 1. This parameter is also depending on the public space existence and road types.

6) Road types (Rt): The risk values for different road types decrease with increasing road capacity, with rural roads having a risk value of 0.8, state highways (SH) at 0.6, two-way national highways (NH) at 0.5, four-way NH at 0.4, six-way NH at 0.3, and eight-way NH at 0.2.

7) Public spaces existence (Ps): The presence of public spaces such as parks, shopping areas, villages, and towns impacts the risk value. A value of 1 assigned if no public spaces exist, indicating higher risk, and a value of 0 if public spaces are present, indicating lower risk.

8) Road environment (Re): The risk values for different road environments vary, segments with villages having a risk value of 0.45, towns at 0.4, and metro areas being the safest at 0.2. More hazardous environments include forests segments with a risk value of 0.7, hilly region segments at 0.9, and plain region segments at 0.5.

9) Road complexity (Rx): The risk values for road complexity decrease as the curve angle increases. Segments with curves between 10°-30° have the highest risk value of 0.9, while curves between 30°-50° have a risk of 0.8, and curves from 50°-70° have a risk of 0.7. For more moderate curves, values range from 0.5 for 70°-100°, 0.4 for 100°-140°, 0.3 for 140°-160°, and the lowest risk of 0.1 is assigned to curves between 160°-180° (straight roads).

10)Availability of CCTV (C): The availability of CCTV significantly enhances safety, with segments equipped with cameras having a risk value of 0, indicating lower risk, while segments without CCTV have a higher risk value of 1, reflecting increased safety concerns.

11)Traffic condition (Tc): The traffic conditions make significate effect on the risk factors. Red, indicating a higher presence of people, is the safest with a risk value of 0.3. Orange represents a moderate risk with a value of 0.6, while blue, signifying fewer co-travelers, is the most hazardous with a risk value of 0.8.

12)Weather condition (Wc): Weather conditions significantly affect route safety, with accidents more likely in adverse conditions. Rainy weather has the highest risk value at 0.8, followed by foggy conditions at 0.7. Cloudy weather presents a moderate risk with a value of 0.5, while sunny weather offers the safest conditions with the lowest risk value of 0.3.

13)Road conditions (Rc): Poor road conditions, characterized by ridges and troughs, increase the risk of accidents (value 0.8), whereas plain roads are safer (value 0.2). These values are fixed for each segment on the route.

14)Time (t): Risk values vary throughout the day, with early morning presenting the highest risk at 0.9 due to factors like reduced visibility and increased fatigue. Morning conditions have a risk value of 0.5, while the risk decreases to 0.4 in the afternoon. Evening and midnight have similar risk values of 0.3 and 0.7 respectively, reflecting different factors such as changing light conditions and reduced alertness.

C. Finding Risk Factors

Finding the risk factors for safe human routing involves analysing a combination of static and dynamic parameters to identify potential hazards and vulnerabilities in a given route. The risk factors are identified for the available routes from the source to the destination. The detailed calculation is provided in the implantation section 4.A.

D. Route Optimization

Finally, the safe route is identified using the risk factors calculated for all routes. The safe route measurement and explanation is provided in Section IV(B) This approach ensures that the routing system enhances safety for all users under a variety of conditions.

IV. IMPLEMENTATION

The safety of a travel route is influenced by various factors, which can be broadly categorized into static and dynamic parameters. Static parameters are those that do not change frequently and include factors such as the type of vehicle, the travelers age, and the road environment. Dynamic parameters, on the other hand, are subject to change over time and include traffic conditions, weather, and road conditions.

A. Risk Factor Calculation

For every source and destination pair, multiple routes can typically be identified, each offering a different path between the two points. These routes are referred to as R_j, where $1 \leq j \leq m$, with m representing the total number of possible routes.

To ensure safety and optimize the selection process, it is essential to calculate the risk factor associated with each possible route. As said in Section III(A), each route R_j is divided into smaller, manageable segments of 100 meters, denoted as S_i. Segmenting the route in this way allows for a detailed and accurate analysis of the risk factors associated with each segment of the journey.

The risk factor for each segment, S_i, is determined by analyzing a combination of static and dynamic parameters. The Static Risk Factor (S_{RFi}) for ith segment is calculated as the average value of ten specific static parameters.

$$S_{RF_i} = \frac{v+g+a+n+L+R_t+P_s+R_e+R_x+C}{10} \quad (1)$$

The Dynamic Risk Factor (D_{RFi}) for each segment S_i is calculated by considering four key parameters that reflect the changing conditions such as traffic, weather, road condition and time of travel of the route.

$$D_{RF_i} = \frac{T_C+W_C+R_C+t}{4} \quad (2)$$

Hence, the Risk Factor (RF_i) of the i^{th} segment is determined by averaging both the Static Risk Factor (S_{RFi}) and the Dynamic Risk Factor (D_{RFi}).

$$RF_i = \frac{S_{RF_i}+D_{RF_i}}{2} \quad (3)$$

This approach ensures that the RF_i reflects a complete assessment of the segment's safety, taking into account both the constant, essential risks associated with static parameters and the fluctuating risks introduced by dynamic conditions. By calculating the RF_i for each segment, the overall safety of the route can be accurately evaluated by summing all segments' risk factors as follows:

$$R_j = \frac{\sum_{i=1}^{N} RF_i}{N} \quad (4)$$

The risk factor for the j^{th} route from the source to the destination is denoted as R_j. This factor represents the level of risk associated with that specific route, considering static and dynamic factors. By quantifying R_j, the overall safety of each route can be assessed, which is crucial for optimizing travel and minimizing potential risks during journey.

B. Route Optimization

The safest route (SR) is determined by evaluating the risk factors associated with all identified routes. By analyzing the calculated risk factors, the route with the lowest risk is identified as the safest. This process involves comparing each route's risk factor to ascertain which one presents the least potential for danger, thereby ensuring the most secure travel option.

$$SR = min(R_j) \quad \text{where } 1<j<m \quad (5)$$

The implementation of this approach is designed to identify the safest route by thoroughly evaluating all relevant parameters from the available routes. By integrating both static and dynamic factors, such as vehicle type, road conditions, lighting, real-time traffic, and weather, the system ensures that each route recommendation prioritizes safety. This methodology not only identifies the safest possible routes but also encourages travelers to follow to these recommendations, thereby enhancing overall travel security and reducing potential risks.

V. RESULTS AND DISCUSSION

In this section, we present analysis of the multi-factor risk assessment and route optimization methodology applied to various identified routes between source and destination. This section explores the effectiveness of the proposed system in identifying and recommending the safest routes by evaluating the impact of static and dynamic parameters on travel safety.

To implement our proposed methodology, we selected Maragathapuram (near Villupuram), Tamil Nadu, as the source and Parvathipuram, Vadalur, Tamil Nadu, as the destination. Parvathipuram is situated in the Vadalur town area. We considered five distinct routes from Maragathapuram to Parvathipuram, all with similar distances but varying slightly in their specifics. These routes traverse diverse topographies, including rural villages, towns, state highways (SH), and national highways (NH), encompassing both two-way and four-way roads. Additionally, the routes include sections passing through rural town near the destination. The routes were partitioned based on road types, and details are provided in Table II.

TABLE II. POSSIBLE ROUTES AND PARTITIONS FROM SOURCE TO DESTINATION

Sl. No.	Route Number	Partition Type (Road Type)	Partition Size (km)	Number of segments
1	1	Rural Village	3.7	37
2	1	NH38-4 ways	5.3	53
3	1	SH68	17	170
4	1	NH36- 2 ways/ 4-ways	23.5	235
5	1	NH532- 4ways	1	100
6	1	Rural Twon	0.8	80
7	2	Rural Village	4.6	46
8	2	Bye Pass Road - 4 ways	9.7	87
9	2	NH36- 2 ways / 4 ways	38.3	383
10	2	NH532- 4ways	1	100
11	2	Rural Twon	0.8	80
12	3	Rural Village	4.3	43
13	3	NH38-4 ways	3.5	35
14	3	NH38-Town	4.2	42
15	3	NH332-2 ways	5	50
16	3	NH36- 2 ways / 4 ways	41.3	413
17	3	NH532- 4ways	1	100
18	3	Rural Twon	0.8	80
19	4	Rural Village	3.7	37
20	4	NH38-4 ways	10.3	103
21	4	SH9	17.3	173
22	4	NH36- 2 ways/ 4-ways	23.5	235
23	4	NH532- 4ways	1	100
24	4	Rural Twon	0.8	80
25	5	Rural Village	3.7	37
26	5	NH38-4 ways	16.4	164
27	5	SH602	27.9	279
28	5	NH36- 2 ways/ 4-ways	11.4	114
29	5	NH532- 4ways	1	100
30	5	Rural Twon	0.8	80

For the route analysis from Maragathapuram to Parvathipuram, Route 1 includes rural village road, NH38, SH68, NH36, NH532, and a rural town segment. Route 2 features rural village road, a four-lane bypass, NH36, NH532, and a rural town. Route 3 starts with rural village road, NH38, NH38-Town, NH332, NH36, NH532, and ends in a rural town. Route 4 consists of rural village road, NH38, SH9, NH36, NH532, and a rural town segment. Route 5 includes rural village road, NH38, SH602, NH36, NH532, and concludes with a rural town. All five routes start from the same rural village road with little variation due to connect with next partition and end with NH532 and rural town segments of same distance.

C. Risk Factor Analysis

Based on the partition details provided in the Table II and values fixed for parameters in the section 3.B, we have simulated values for all the parameters of all partitions by seriously considering the partitions types. The chosen mode of transport is a car, with four passengers (three men and one woman), and the average age-related risk factor for the group is 0.4. The data was simulated using default values for three parameters: lighting facility was assigned 0 risk due to daytime travel, weather condition was set to sunny, and the travel time was set to afternoon. The remaining parameter values were fixed based on partitions and dependent parameters.

The risk factor is calculated for each 100-meter segments using the Eq. (3) with help of Eq. (1) and Eq. (2). The overall risk factor for the route is calculated using the Eq. (4).

The Fig. 2 shows the risk factors of all segments of Route-1. For Route-1, risk factors across partitions range from a minimum of 0.29375 to 0.34625 and a maximum of 0.40125 to 0.59125. Average risk factors vary between 0.35975 and 0.478885135, with specific averages of 0.478885135, 0.422900943, 0.458838235, 0.432356383, 0.35975, and 0.4253125. This variation reflects inconsistencies in risk levels along the route, particularly in village environments.

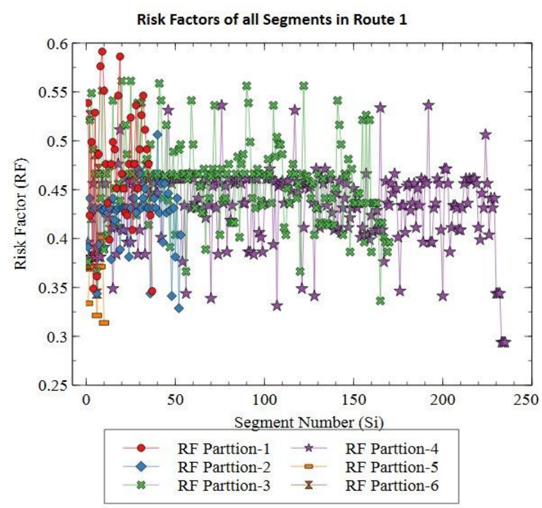

Fig. 2. Risk factors of all segments in route-1.

Fig. 3 presents the risk factors along Route-2. The minimum risk factors for Route-2 range from 0.29375 to 0.34625, while the maximum values vary between 0.40125 and 0.59125. The average risk factors across the five segments are 0.4748, 0.4553, 0.4391, 0.3598, and 0.4253, respectively.

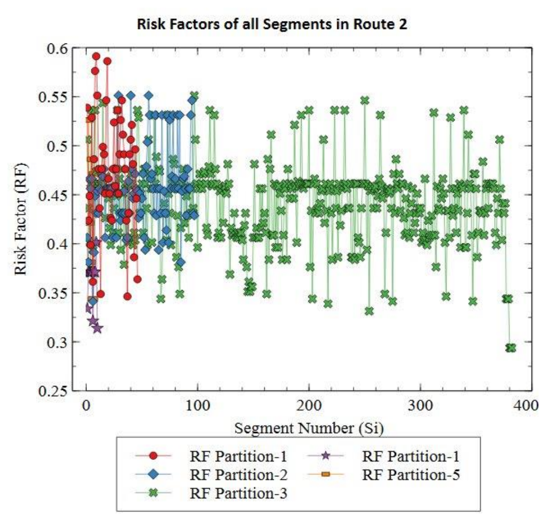

Fig. 3. Risk factors of all segments in route-2.

Route-3 consists of seven partitions and risk factors are calculated. Fig. 4 illustrates the risk factors across all segments of Route-3. The minimum risk factors range from 0.27875 to 0.36125, while the maximum values range from 0.40125 to 0.59125. The average risk factors for the seven segments are 0.4830, 0.4418, 0.3616, 0.4217, 0.4406, 0.3598, and 0.4253, respectively.

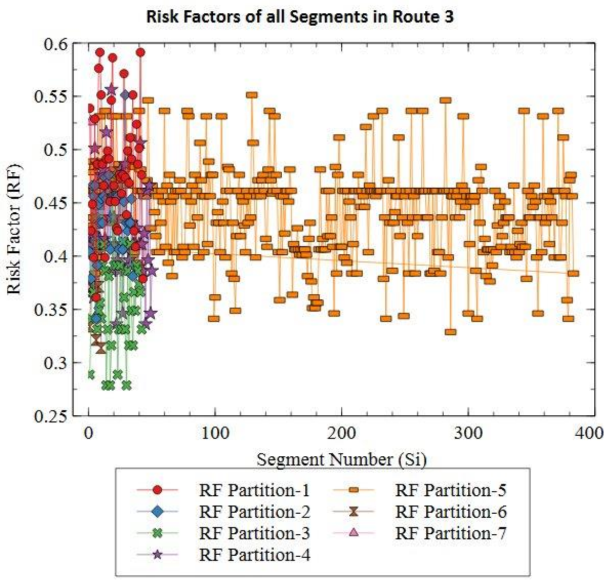

Fig. 4. Risk factors of all segments in route-3.

Route-4 consists of six segments, with the same combinations of road types as discussed in Route-1, but with variations in the distances of state and national highways. It follows a different path compared to Route-1.

Fig. 5 shows the risk factors for all six segments of Route-4, as outlined in Table II. The minimum risk factors range from 0.29375 to 0.34625, while the maximum values range from 0.40125 to 0.59125. The average risk factors for the six segments are 0.4782, 0.4208, 0.4463, 0.4324, 0.3598, and 0.4253, respectively.

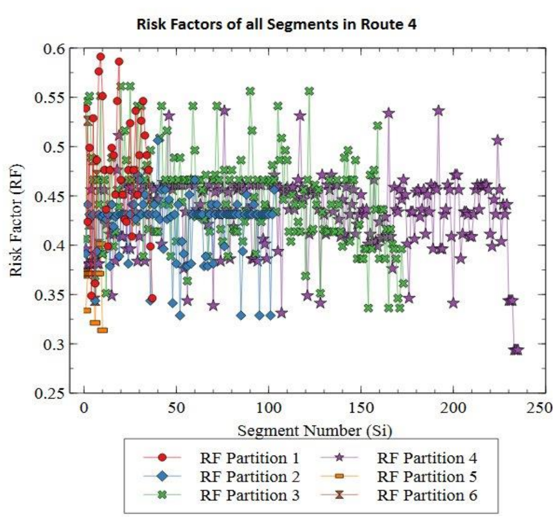

Fig. 5. Risk factors of all segments in route-4.

Similarly, the risk factors for the six segments of Route-5, where the state highway is the major contributing partition, have been calculated. Fig. 6 illustrates the risk factors for all segments of six partitions along Route-5. The minimum risk factors range from 0.29125 to 0.34875, while the maximum values range from 0.33375 to 0.53875. The average risk factors for the six segments are 0.4819, 0.4182, 0.4770, 0.4287, 0.3598, and 0.4253, respectively.

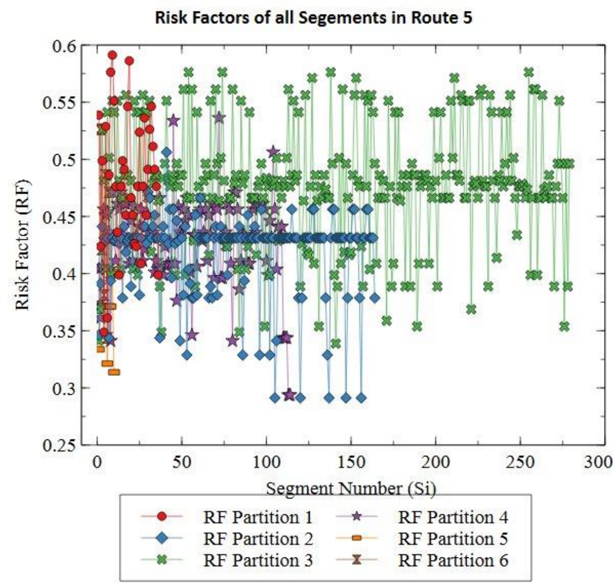

Fig. 6. Risk factors of all segments in route-5.

The risk factors for all partitions across all routes are shown in Fig. 7. The risk factors for the first partition are nearly identical across all routes due to minimal distance variation on the routes. Likewise, the risk factors for the last two partitions are the same, as these partitions remain consistent across all routes.

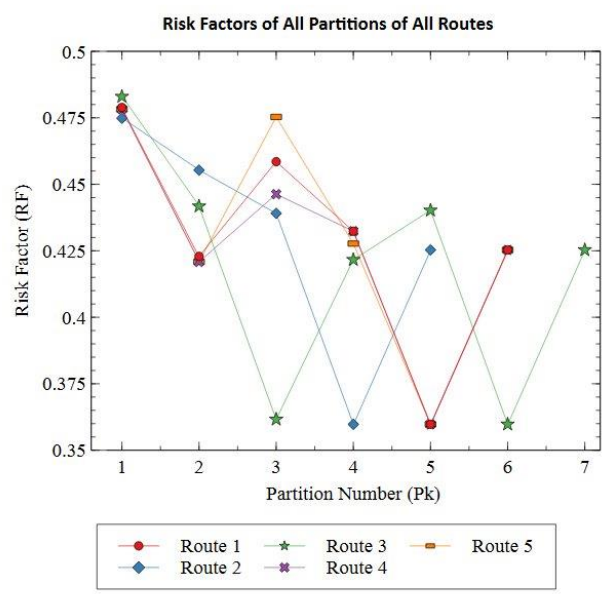

Fig. 7. Risk factors of all partitions in five routes.

The average static, dynamic, and final risk factors for all five routes are shown in Fig. 8. It illustrates that the static risk factor is higher than the dynamic risk factors for all routes except Route 3, which has a larger town area compared to the other routes.

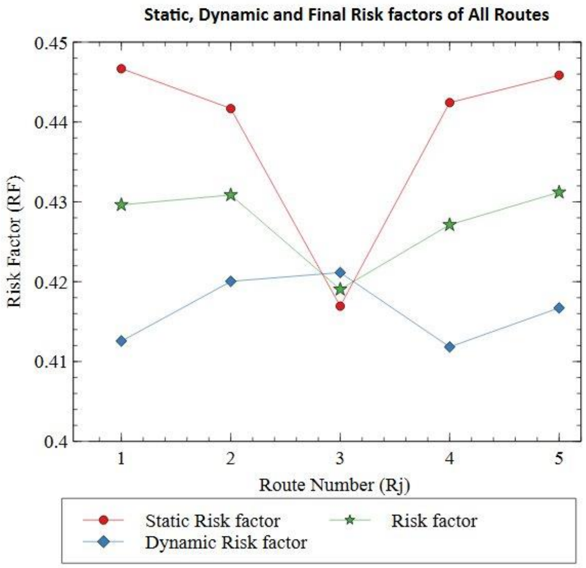

Fig. 8. Static, dynamic and final risk factors of all routes.

D. Safe Route Identification

The safest route is determined using Eq. (5), which calculates the route with the minimum risk factor among the studied routes. In this study, we analyzed five possible routes as given in Table II, each with varying partitions. Fig. 9 presents the risk factor values for all five routes. Route 3 has the lowest risk factor compared to the others.

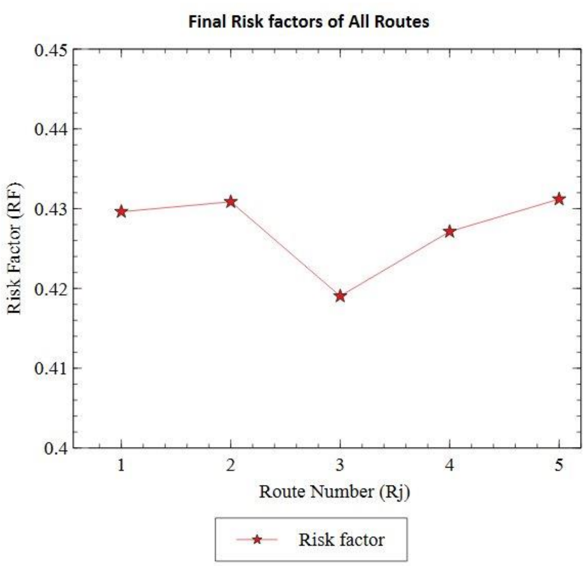

Fig. 9. Risk factors of all routes.

The reduced risk for Route 3 is attributed to several factors. This route passes through more town areas, which typically have better infrastructure and safety measures such as lighting and traffic control. Additionally, Route 3 follows longer stretches of national highways, known for their higher safety standards and better road conditions. Finally, the higher population density along this route also contributes to its lower risk, as densely populated areas have less threatened from the attackers.

The risk factors of five routes are evaluated under varying weather conditions, while maintaining the other parameters constant. Fig. 10 illustrates the impact of different weather conditions on the risk factors across all five routes.

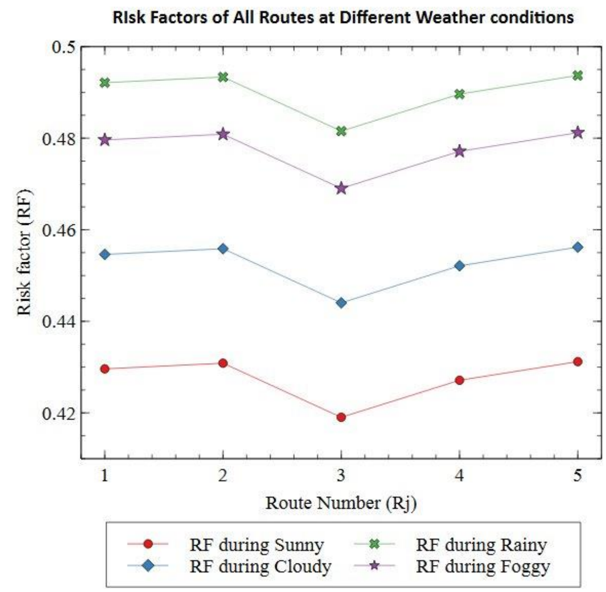

Fig. 10. Risk factors at different weather conditions.

Route 3 consistently offers the lowest risk factor across all weather conditions, as it passes through more densely populated areas.

The time of travel is also taken into account when calculating the risk factors for all five routes. For daytime travel, including morning, afternoon, and evening, the lighting facility value is set to 0, as natural light is sufficient. For night time travel, the lighting facility value is determined based on the presence of public places along the route and the type of route partitions. This adjustment reflects the availability and effectiveness of artificial lighting in reducing risk during night time. Fig. 11 illustrates how travel time influences the overall risk factor calculation across different routes.

The results indicate that Route 3 is the most optimal for daytime travel, yielding the lowest risk factors due to its natural lighting and favorable conditions during daylight hours. Conversely, for nighttime travel, the Route 2 is found to be the safest, offering the lowest risk factors. This is primarily attributed to better lighting infrastructure, the presence of public spaces, and well-defined route partitions that enhance visibility and safety during night hours. These findings highlight the importance of adapting route selection based on the time of travel to minimize risk.

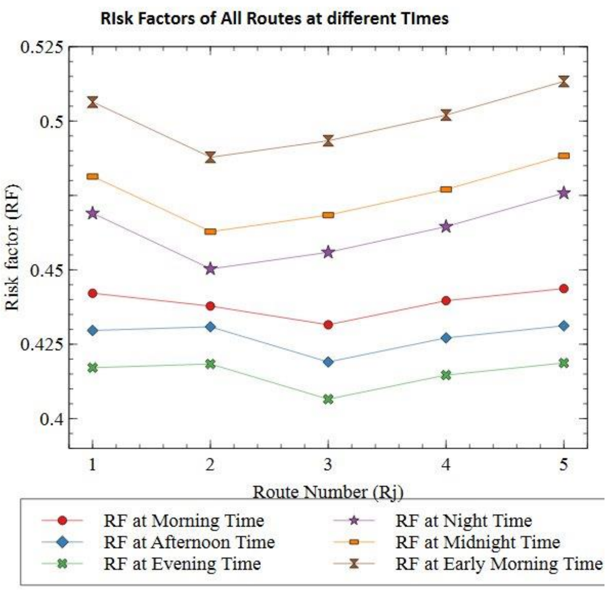

Fig. 11. Risk factors at different travel time.

The results demonstrate the effectiveness of the proposed model in identifying safe travel routes. The inclusion of both static and dynamic parameters ensured a risk assessment, making the model suitable for safe human travelling on the optimal route predicted by the proposed model.

VI. Conclusion

In conclusion, this study presents a multi-factor risk assessment and route optimization methodology aimed at improving travel safety based on the chosen sources and destination places. By incorporating both static and dynamic factors, the system effectively identifies the safest routes based on calculated risk factors. Our analysis reveals that Route 3 is the safest for daytime travel, while Route 2 is optimal for nighttime travel due to better lighting and route partitions. The granular assessment of 100-meter segments along the routes highlights the significant impact of environmental and infrastructural factors on travel safety, including artificial lighting, time of travel, and weather conditions. This adaptable framework, influence widely applicable risk parameters, demonstrates the potential for broader real-world applications in dynamic and changing road networks, ensuring safer route recommendations.

In future work, we aim to enhance the system by integrating real-time data sources, such as live weather updates, traffic congestion reports, and road maintenance data, to provide even more accurate risk assessments. Additionally, we plan to incorporate machine learning techniques to continuously improve the precision of risk predictions based on observed outcomes. By doing so, the system can become more robust and reliable in its route optimization recommendations.

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