ARCHIVES OF TRANSPORT *ISSN (print):* *0866-9546*
Volume 73, Issue 1, 2025 *e-ISSN (online):* *2300-8830*
DOI: *10.61089/aot2025.818s6t27*

OPTIMIZING URBAN TRANSPORTATION NETWORK RELIABILITY BY ANALYZING ROAD TRAFFIC ACCIDENTS

J. Isaac PEMBERTHY-R.[1], Eduard GAÑAN-CARDENAS[2]

[1,2] Instituto Tecnológico Metropolitano, Facultad de Ciencias Económicas y Administrativas, Medellín, Colombia

Abstract:

Urbanization has led to increased traffic congestion and road traffic accidents (RTAs), significantly impacting public health, urban mobility, and the efficiency of transportation systems. RTAs disrupt road transport networks, reducing their reliability and performance metrics, which are critical for economic and social activities. This study addresses these challenges by integrating statistical analysis and optimization modeling to enhance the reliability of urban transportation networks through targeted interventions. The proposed methodology builds upon the reliability model by Jovanović Dragan et al. (2011), utilizing statistical analysis of historical RTA data to evaluate transport network reliability. This assessment informs of a linear programming (LP) optimization framework designed to allocate intervention budgets effectively. The LP model incorporates road importance, defined by traffic volume, prioritizing investments on high-impact roads to mitigate RTAs and improve overall network performance. The methodology is demonstrated through a case study in Medellín, Colombia, a city facing significant congestion and high RTA rates (average 100 daily). Using geolocated accident data (2017–2019) and vehicle usage metrics, two model variations were tested: one including road importance and another without. Both models yielded efficient solutions using standard optimization solvers with minimal computational time. Findings demonstrate that the model incorporating road importance provides more targeted budget allocations, aligning better with practical priorities by focusing interventions on the busiest and least reliable road segments. This study highlights the value of combining RTA analysis and network reliability perspectives for data-driven strategic transportation planning. The approach offers actionable insights for policymakers and urban planners seeking to reduce accidents and enhance urban mobility through optimized resource allocation. Future research could expand this framework to include other disruption types (e.g., natural disasters) or validate intervention effectiveness through detailed simulation modeling.

Keywords: *urban mobility, transport network reliability, urban transport network optimization, road traffic accidents, operations research, linear programming*

To cite this article:

Pemberthy-R., J.I., Gañan-Cardenas, E., (2025). Optimizing urban transportation network reliability by analyzing road traffic accidents. Archives of Transport, 73(1), 155-177. https://doi.org/10.61089/aot2025.818s6t27

Contact:
1) jorgepemberthy@itm.edu.co [https://orcid.org/0000-0002-0019-578X] – corresponding author; 2) eduardganan@itm.edu.co [https://orcid.org/0000-0003-2070-2651]

1. Introduction

Critical infrastructure, encompassing transportation, water supply, telecommunications, and energy systems, forms the backbone of modern societies, underpinning economic activities and overall quality of life (Muriel-Villegas et al., 2016). Among these, transport networks play a central role in fostering dynamic economic development, particularly in urban areas where increasing population densities have intensified challenges associated with traffic congestion, pollution, accidents, and resource inefficiencies (Jain & Jain, 2021). The reliability of transport networks (RTN) is thus critical for sustaining economic exchanges and social interactions, directly impacting connectivity and mobility (Soltani-Sobh et al., 2016).

Reliability in engineering is traditionally defined as the probability of a system performing its intended function under specific conditions for a designated time (Bimpou & Ferguson, 2020; Muriel-Villegas et al., 2016). However, applying this concept to transport networks introduces complexities due to external disruptions such as natural hazards, traffic congestion, infrastructure failures, and notably, road traffic accidents (RTAs). Moreover, users' perceptions of reliability, shaped by factors like travel time variability and connectivity, often differ from conventional system-focused reliability metrics (Lam et al., 2014).

Urban road networks face frequent disruptions caused by RTAs, which are a leading cause of fatalities globally, particularly in middle-income countries like Colombia (Geneva: World Health Organization, 2018). These incidents reduce network capacity, increase travel times, compromise user safety, and diminish overall network reliability. Addressing these multifaceted issues requires comprehensive approaches that integrate accident frequency analysis with strategies to enhance network resilience and performance.

Research in RTN typically focuses on evaluating system vulnerability and optimizing connectivity through statistical and simulation-based models (Ravi Sekhar et al., 2013; Soltani-Sobh et al., 2015). Concurrently, studies on RTA employ data analysis to identify accident hotspots, predict patterns, assess impacts, and design preventive measures (Gutierrez-Osorio & Pedraza, 2020; Wallace et al., 2021). While valuable independently, integrating these perspectives offers a more holistic approach, enabling the development of targeted strategies that simultaneously enhance urban mobility and reduce accident rates.

This paper introduces an innovative framework that synergizes statistical analysis and optimization modeling to address both RTN reliability and RTA frequency. We adapt a statistical model to evaluate transport network reliability by incorporating historical RTA data as indicators of disruption. This reliability assessment then serves as a key input into a linear programming (LP) model designed to optimize the allocation of limited budgets for road interventions aimed at accident reduction. By incorporating a measure of road importance, defined by usage frequency (traffic volume) alongside accident incidence, the proposed approach ensures efficient and targeted resource allocation to enhance both safety and network reliability.

The methodology's practical application is demonstrated through a case study in Medellín, Colombia. This city presents significant mobility challenges, including ranking among the most congested globally (INRIX, 2020) and experiencing an average of 100 daily traffic accidents. Using geolocated accident data from 2017–2019 and vehicle usage metrics, two model variants are tested and compared: one incorporating the road importance factor and another treating all roads equally from an importance perspective. Deterministic analyses illustrate the efficacy of the proposed models in guiding intervention decisions to reduce accidents and improve network reliability from a strategic planning standpoint. This study underscores the critical importance of integrating RTN and RTA perspectives into decision-making processes for urban transportation planning. The findings provide actionable insights into optimizing intervention budgets to enhance road safety and overall mobility. The paper is organized as follows: Section 2 reviews relevant literature, Section 3 provides context and data for the case study, Section 4 details the methodologies including the reliability assessment and optimization models, Section 5 presents experimental results, Section 6 discusses the findings, contributions, and limitations, and Section 7 concludes with key takeaways and directions for future research

2. Literature review

The reliability and optimization of transportation networks are crucial areas of research, driven by the increasing complexities of urban mobility and the significant societal costs associated with network disruptions. Research spans multiple facets, including defining reliability, modeling disruptions, analyzing road traffic accidents (RTAs), and developing optimization strategies for network improvement.

2.1. Transportation network reliability (RTN)

RTN is often evaluated using user-centric metrics like travel time and cost (Ravi Sekhar et al., 2013; Soltani-Sobh et al., 2015). Lam et al. (2014) emphasize the importance of RTN as a field, noting the distinction between engineering definitions of reliability and user perceptions influenced by factors like travel time variability. Network vulnerability is a related concept, though lacking a universal definition (Muriel-Villegas et al., 2016). Practical approaches often measure network availability or the probability of uninterrupted performance. Disruptions stem from various sources, including infrastructure failures, natural disasters, congestion, and RTAs. RTAs, in particular, are frequent disruptors in urban environments, significantly impacting network performance and safety (Geneva: World Health Organization, 2018). The model proposed by Jovanović Dragan et al. (2011), which forms a basis for our reliability assessment, specifically uses statistical analysis of RTAs to quantify the reliability of road segments, providing a direct link between accident occurrence and network performance metrics.

2.2. Analysis of road traffic accident (RTA)

The increasing frequency and impact of RTAs have spurred a significant body of research focused on understanding their causes, patterns, and consequences to develop effective prevention and mitigation strategies (Gutierrez-Osorio & Pedraza, 2020). Studies often employ behavioral analysis to model accident determinants and predict impacts (e.g., Novikov et al., 2020; Rolison, 2020). Statistical modeling, including classical techniques like binomial regression, multiple linear regression, and Poisson or Negative Binomial models (Briz-Redón et al., 2021), is frequently used to correlate accident frequency with factors such as road geometry, traffic flow, environmental conditions, and driver behavior. Spatial analysis techniques are also employed to identify high-risk locations or 'hotspots' (Pineda-Jaramillo & Arbeláez-Arenas, 2021). Recent advancements incorporate machine learning and data mining approaches, such as decision tree analysis (Figueira et al., 2017), support vector machines (Li et al., 2016), and other non-parametric methods (Lee et al., 2017; Bauer et al., 2021), to extract complex patterns and improve predictive accuracy regarding accident occurrence and severity. Research also explores the effectiveness of interventions, such as road design improvements (Wallace et al., 2021), specific strategies for developing countries (Schoeman, 2018), and governmental policies like congestion charging or penalty point systems (Green et al., 2016; Martínez-Gabaldón et al., 2020; Mitsakou et al., 2019). Furthermore, the impact of RTAs on network performance metrics like average travel times (Kaddoura & Nagel, 2018) and overall urban mobility (Sun et al., 2018) is a critical area of investigation. Intelligent Transportation Systems (ITS) play a growing role, focusing on technologies for accident prediction and detection to optimize emergency response and mitigate traffic impacts through user guidance (Jain & Jain, 2021; Oskarbski, 2017).

2.3. Optimization in transportation networks

Optimization techniques are widely employed in transportation planning and management. Classical operations research problems find application in RTA contexts; for instance, the facility location problem is used to optimize the placement of emergency services like ambulance depots considering accident hotspots (Castañeda & Villegas, 2017; Mohri & Haghshenas, 2021; Wajid et al., 2020), while the shortest path problem is adapted to develop efficient ambulance routing models under stochastic traffic conditions often caused by accidents (Jose & Vijula Grace, 2020; Wen et al., 2019).

More broadly, optimization addresses resource allocation, network design, and traffic management. Linear programming (LP), foundational to this study, has a long history in solving problems with linear objectives and constraints (Dantzig, 1957). The knapsack problem formulation, often solved using dynamic programming (Bellman, 1957) or LP for continuous versions, is particularly relevant for budget allocation tasks like the one addressed here.

However, the increasing complexity of transportation systems necessitates more advanced techniques. Modern approaches often move beyond traditional LP. Metaheuristics like Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Differential Evolution (DE) are frequently used for complex, large-scale, or non-linear problems such as traffic signal control, vehicle routing, and incident detection (Srinivasan et al., 2003). For instance, Srinivasan et al. (2003) effectively applied PSO for traffic incident detection. Akopov et al. (2021) utilized a parallel GA for simulation-based optimization in autonomous transport systems, demonstrating the synergy between metaheuristics and simulation. Nonlinear programming (NLP) addresses non-linear objectives or constraints common in traffic flow modeling. Multi-objective optimization is also vital for balancing competing goals like minimizing travel time, emissions, and costs while maximizing safety (Sayyadi & Awasthi, 2020). While powerful, these advanced methods often entail greater computational cost and complexity compared to LP.

2.4. Research gap and contribution

While extensive research exists on RTN, RTA analysis, and transportation optimization independently, there is a need for integrated approaches that explicitly link historical accident data, network reliability assessment, and strategic budget allocation for interventions. Many optimization studies focus on operational aspects (e.g., real-time traffic control) or use simulation without directly grounding the optimization objective in statistically derived reliability metrics based on actual accident occurrences. Furthermore, while advanced optimization techniques like GA and PSO offer powerful capabilities, simpler models like LP can be highly effective and computationally efficient for specific strategic planning problems, such as the budget allocation task addressed here, especially when the primary goal is to prioritize interventions based on clear metrics like historical reliability and road importance.
This study contributes by:

- Integrating a statistical RTA-based reliability assessment (adapted from Jovanović Dragan et al., 2011) directly into an optimization framework.
- Developing an LP model specifically for strategic budget allocation for RTA mitigation interventions, incorporating road importance based on traffic volume.
- Demonstrating a computationally efficient approach suitable for practical planning purposes, providing a clear and interpretable method for prioritizing investments based on data-driven reliability and importance metrics.
- Providing a case study in a high-congestion, high-accident urban environment (Medellín), showcasing the practical applicability of the framework.

3. Case study

This study was carried out in Medellín, the second most populated city in Colombia. Medellín is the capital of the state of Antioquia and is in the Aburrá Valley. This valley is composed of 10 cities that form the Metropolitan Area. Medellín is the most populated city in the valley, with a population of nearly 2.5 million of the nearly 4 million inhabitants of the valley (DANE, 2019). Medellín is located in the center of the valley and is the city that generates the most employment in the entire metropolitan area, which makes it the city that is transited by the most people on weekdays. Today, Medellin ranks 22nd among the most congested cities in the world according to the INRIX index, with a total of 62 hours lost in congestion per year (INRIX, 2020). According to the city's mobility survey conducted in 2017, Medellín is the destination of 71% of the trips that people made in the metropolitan area throughout the day, with a total average of 4.3 million daily trips by different means of transportation (Area Metropolitana de Medellín, 2017). This excludes trips that pass through the city but whose end destination is not within it. This current reality of the city shows the need to work on finding ways to improve the mobility situation.

3.1. Data base

In Medellin, there are different databases available. The information we used throughout the study is based mainly on the city's road infrastructure, RTA records, and a database of the number of vehicles using the road infrastructure.

3.1.1. Roadways data

The distribution of roads in Medellin is simple. There are a total of 1,030 roads distributed in different classes. In this case study, we are specifically interested in the busiest roads in the city, which are classified as primary roads, urban highways or city crossings, and secondary roads. The main reason for our interest in this class of roads is the fact that they are the roads of main use throughout the city, and on which most accidents occur. The classification by road class is shown in Table 1.

Table 1. Classification of roads in Medellin

Type of road	Number of roads	Percentage (%)
Secondary road	328	31.84%
Primary road	260	25.24%
Rural secondary road	255	24.76%
Rural primary road	145	14.08%
National first order road	15	1.46%
Second order national route	11	1.07%
Urban highway or cross-road	10	0.97%
National third order route	3	0.29%
Railroad track	3	0.29%
Total	1,030	100.00%

3.1.2. RTA data

The accident database is obtained from the public repositories of the Mayor's Office of the City of Medellín (Alcadía de Medellín, 2020). It includes only accidents occurring in the Medellín area. It does not include the areas of other cities that are part of the metropolitan area. The available data records from 2017 to February 2021 show a total of 172,593 accidents. Each record has a date, time, and location with coordinates and classification into 3 categories according to its severity: accidents with injury (55.2%), only material damage (44.21%) or with one or more deaths (0.59%). 7.3% of the records have errors in the filling out of the location coordinates, so they had to be eliminated. When analyzing the database, it was necessary to disregard the records for the years from 2020 to 2021, since they show better results generated by the atypical period of the pandemic generated by Covid-19. As can be seen in Figure 1, the number of accumulated accidents decreased because of the lockdown. However, the objective of this study is to contemplate data adjusted to reality. Therefore, the study only includes the analysis of the RTA data period between the years 2017-2019, which left 133,406 recorded accidents. In addition to the geographic location of each accident, the database includes some additional variables as shown in Table 2.

3.1.3. Vehicle count data

Medellín employs an advanced traffic control system using live cameras to monitor various road conditions throughout the day. These systems enable vehicle counts at specific points. This information is considered in the study to represent road importance, as it quantitatively indicates the number of vehicles using a road daily.

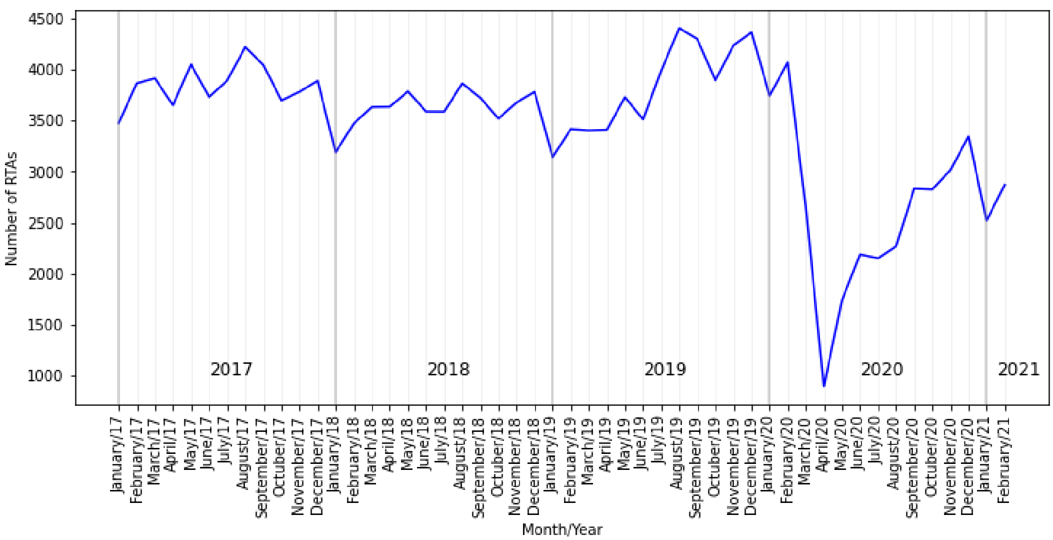

Fig. 1. Accumulated RTA over the period 2017 - February 2021 in Medellin

Table 1. Distribution of RTA

Variables		Number of RTA	Percentage (%)
Year	2017	45,370	34.01%
	2018	42,781	32.07%
	2019	45,255	33.92%
Day	Monday	19,214	14.40%
	Tuesday	21,031	15.76%
	Wednesday	20,257	15.18%
	Thursday	19,899	14.92%
	Friday	21,395	16.04%
	Saturday	19,144	14.35%
	Sunday	12,466	9.34%
RTA type	Crash	91,220	68.38%
	Other	14,123	10.59%
	Hit and run	11,802	8.85%
	Occupants fall	11,453	8.59%
	Rollover	4,769	3.57%
	Fire	21	0.02%
	Fall of an occupant	17	0.01%
	Crash and run over	1	0.00%
RTA location	Road section	82,380	61.75%
	Intersection	24,903	18.67%
	Lot or Property	19,139	14.35%
	Roundabout	4,123	3.09%
	Elevated pass	971	0.73%
	Bridge	701	0.53%
	Cycle Path	542	0.41%
	Underpass	460	0.34%
	Level crossing	92	0.07%
	Tunnel	48	0.04%
	Pontoon	24	0.02%
	Crosswalk	22	0.02%

The use of real data is crucial in this type of study, especially when collected via reliable sensors on the roads. However, using such information depends directly on the locations and number of sensors deployed throughout the city. In Medellín, vehicle counts are available for only a few primary roads, which limits the ability to include other roads in the study if this information is required.

Figure 2 illustrates the roads with the highest accident frequency in 2017. Given the limitations in vehicle count data described above, the study necessarily focused on a subset of primary roads. Consequently, two modeling approaches were analyzed: one incorporating vehicle count information for available primary roads, and another excluding this importance factor, allowing for a comparison of results between the two methods.

4. Methodology

4.1. Data analysis

To establish what information is useful for the development of measurement or optimization models, it is essential to perform two stages of evaluation of the available information. Before any experimentation stage, we evaluate the available data to meet two essential requirements. The first focuses on testing the compatibility of the behavior of the data with the selected models. In this case, we focused on the reliability measurement model of the transport network model, since this model is based on the assumption that the distribution of RTA follows a Poisson distribution, or in other words, that the times between RTA behave following exponential distribution. The second requirement focuses on data quality and compatibility between the different databases. In short, we evaluate the behavior, the quality of the data, and the compatibility of the different databases used.

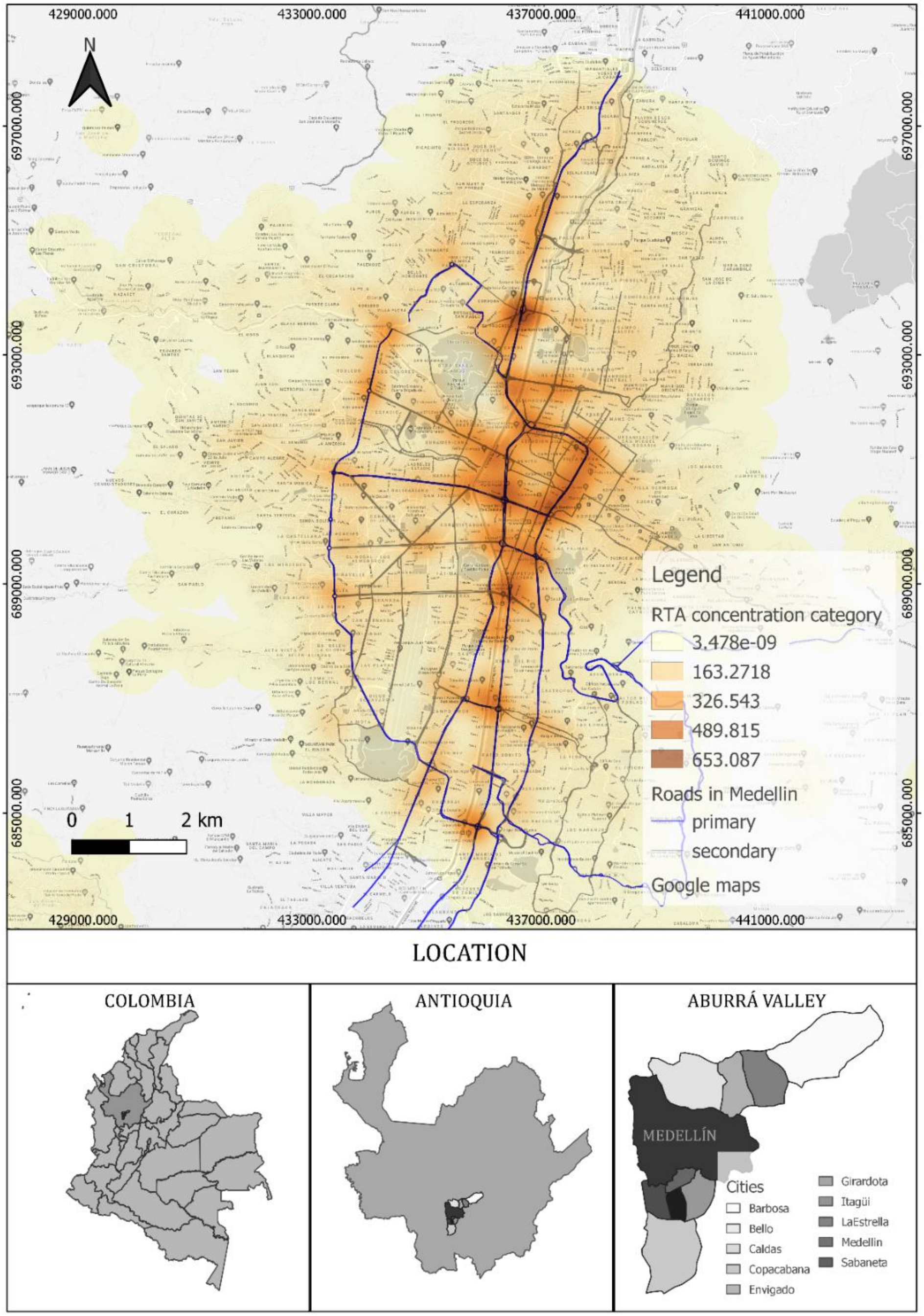

Fig. 2. Medellin RTA Heatmap in 2017

4.2. Reliability transport network model

The model used to measure the reliability of the transport network is proposed by Jovanović Dragan et al., (2011). This model successfully proposes fitting *Poisson* distribution to describe the behavior of RTA events. This model considers each road as a complex system composed of n units or sections, where the interruption of traffic flow in any unit causes the interruption of traffic flow in the entire road. The model proposed for road reliability in the study contemplates long road sections as part of the complex system. Specifically, they contemplate sections between 4 and 18 km long on an interurban road, to measure the reliability of the whole road. In our case, we consider the study only of urban roads with extensions no longer than 16 km. Therefore, the use of the model for our case is defined for each road, and the adaptation of the model to the reliability of a system is not used when considering the reliability of each section of the road. For this reason, we consider the road as a whole and do not specify sections as the objects of study. For the use of this model, it is assumed that the roads have an independent probability of failure.

According to Jovanović Dragan et al., (2011) a process describing a Poisson distribution is characterized by a λ rate, which is defined as the number of 'events' occurring per unit of time. If the events follow a Poisson-type distribution, then the time between the occurrences of two events (T) can be described by an exponential distribution with parameter λ. Therefore, in the model adopted, all empirical distributions of the duration of the accident-free period can be replaced by exponential distributions. The terminology used in the model is defined below. For more information on the model and its approach, please see the work of Jovanović Dragan et al., (2011).

4.2.1. Defining the model terms

The density function of the distribution of the time between two accidents $f(t)$ $(fi(t) - ith)$ is:

$$f_i(t) = \lambda_i e^{-\lambda_i t} \qquad where\ \lambda_i > 0, t \geq 0 \tag{1}$$

Distribution function $F\ (t)(Fi(t) - i\text{th road})$ of the random variable T (the time between two accidents), is equal to the probability that an accident will occur before the moment t. This function is also called the function of unreliability.

$$F_i(t) = \int_0^\infty f_i(t)dt = \int_0^\infty \lambda_i\, e^{-\lambda_i t}dt = 1 - e^{-\lambda_i t} \tag{2}$$

Using the unreliability function F(t) we introduce the reliability function $R(t)(Ri(t) - i\text{th road})$, as the probability of a time without accidents until the moment t.

$$R_i(t) = 1 - F_i(t) = e^{-\lambda_i t} \tag{3}$$

The mean time between two consecutive accidents T_0 $(T_{0i}(t) - i\text{th road})$ is obtained as a mathematical expectation of the random variable T.

$$T_{0i}(t) = \int_0^\infty R(t)dt = \int_0^\infty e^{-\lambda_i t}dt = 1/\lambda_i \tag{4}$$

The accident frequency $a(t)$ $(a_i(t) - i\text{th road})$ is an important and widely used reliability feature and represents the measure of the current rate of accidents.

$$a_i(t) = \lambda_i = const \tag{5}$$

The expected number of accidents in a certain period $A(t)$ $(A_i(t) - i\text{th road})$ is calculated as:

$$A_i(t) = \lambda_i t \tag{6}$$

where t – the duration of the certain period time expressed in basic time unit as λ.

The purpose of this model is to measure the reliability of each road in each time period. Reliability will be a base parameter in the optimization model.

4.3. Mathematical modeling of the problem

The proposed model is grounded in the knapsack problem, a classic case in combinatorial optimization. This problem was initially formalized by Dantzig, (1957) and later solved using dynamic programming techniques introduced by Bellman, (1957). These foundational contributions established a framework for addressing resource allocation problems under capacity constraints.

The knapsack problem is commonly described as follows: given a set of n items, each with a value v_i and a weight w_i, the objective is to select a subset of these items to maximize the total value without exceeding capacity C of the knapsack. The basic mathematical formulation is:

$$Maximize\ Z = \sum_{i=1}^{n} v_i x_i \tag{7}$$

Subject to:

$$\sum_{i=1}^{n} w_i x_i \leq C \tag{8}$$

$$x_i \in \{0,1\} \quad \forall\ i\ \in \{1, \ldots, n\} \tag{9}$$

where:
x_i is a binary variable indicating whether item i is selected ($x_i = 1$) or not ($x_i = 0$),
v_i represents the value of item i,
w_i is the weight of item i,
C is the maximum capacity of the knapsack.
For our case, we propose adaptations to the classical knapsack problem to address the unique characteristics and requirements of the problem at hand. Given a set of edges, where each edge i is a road within the transport network ($i\ \in\ E$). Each edge is defined as a road and each vertex as intersection between roads, to represent a transportation system network. It is assumed that there is independence between the failures of each edge of the graph. The reliability of an edge i in scenario s in the time t is denoted as $R_i^s(t)$. I_i is defined as the importance of road i, where this parameter is represented by the average number of vehicles traveling on the road per 15-minute interval. There is an intervention cost C_i for each road i that by its nature can have a stochastic behavior, therefore a random value is defined for this parameter with investment limits between $10,000 and $25,000 dollars. In this case, the value of this parameter could be defined depending on the length of the road. However, in many cases, road interventions to mitigate accidents can be implemented at a junction or a signpost, and for this reason, it is difficult to ensure that the cost of the road intervention is proportional to its length. Therefore, this parameter is defined under the condition of randomness. A constant budget of B is defined by the city's mayor's office for road interventions. This budget is specifically defined with the objective of mitigating road accidents. In this case, a theorical value of $250,000 dollars is established to carry out the exercise of the case.
In our case, the decision variable is continuous, representing the percentage of intervention allocated to each road segment. This formulation significantly reduces the computational complexity of the problem, transitioning it from a combinatorial optimization problem to a linear optimization problem. By allowing fractional values, the model achieves greater flexibility and computational efficiency while maintaining the precision required for effective decision-making. This variable is defined as the percentage of fixed intervention cost consumption for each road. This variable is denoted as x_i.
To increase the reliability of the transportation system, it is necessary to increase the reliability of each road independently, or at least to increase the reliability of the worst-measured roads. With this objective, an optimization model is defined that seeks to propose an efficient use of the transportation network intervention budget (B), using a variable (x_i) that defines an intervention percentage of the most important (I_i) and least reliable roads. Due to the nature of the problem, and because of the behavior over time of the road reliability parameter, the model defined includes a set S of three scenarios represented in the years 2017, 2018 and 2019. Table 3 summarizes the terms used in the mathematical formulation of the problem.
Given the restrictions of available data of the vehicle count, the parameter included in the problem was the importance of the road. Two linear programming models were defined for testing and finding solutions. Only the first of these includes the importance parameter. The difference lies in the information that can be used in one model and the other. The first uses accident information that concentrates on a total of 61 of the primary roads. The second model is used considering a total of 118 primary roads that account for around 75% of the accidents that were generated in the various analysis periods. The first mathematical model is represented in the group of equations (10) – (12). The second model is represented in equations (11) – (13)

$$Maximize\ Z = \sum_{i \in E} \sum_{t \in S} I_i \cdot \left(1 - R_i^s(t)\right) \cdot x_i \tag{10}$$

Table 2. Sets, indexes, parameters and decision variables for mathematical formulation

Type	Notation	Definition
Sets	E	Set of edges
	S	Set of scenarios of time intervals S = {2017, 2018, 2019}
Indexes	i	Indexes used to represent every edge or road, i ∈ E
	s	Indexes used to represent every scenario, $s \in S$
Parameters	$R_i^s(t)$	Reliability of road i in the scenario s
	I_i	Importance of road i.
	C_i	Constant cost of intervention of a road i.
	B	Maximum intervention budget of the road network
Decision variable	x_i	Indicates the percentage intervention of road i.

Subject to:

$$\sum_{i \in E} C_i \cdot x_i \leq B \tag{11}$$

$$0 \leq x_i \leq 1 \qquad \forall\, i \in E \tag{12}$$

Equation (10) represents the objective function of the model, which seeks to maximize the intervention of the most important and least reliable roads. Equation (11) defines the B budget consumption constraint available for road interventions. The group of equations (12) defines the order interval in which each decision variable defines its value.

$$Maximize\ Z = \sum_{i \in E} \sum_{t \in S} (1 - R_i^s(t)) \cdot x_i \tag{13}$$

The only difference in this second model is the change in the objective function (13) whereby it does not include parameter I_i, and the restrictions are preserved as those set out in equations (11) and (12). In general, the model is the same, what really changes is the information used in this model versus the initial one. In solving this model, a more significant result can be obtained since it includes most of the accident data for the periods studied.

4.4. Algorithm for solving the optimization problem

The optimization model formulated in Section 4.3 (equations 10-13) is a Linear Programming (LP) problem. The objective function of the model, which seeks the intervention of the most important and least reliable roads, is seeking to maximize the RTN, subject to a budget constraint and bounds on the intervention variables. Given the structure of the problem (linear objective function and linear constraints), standard and efficient algorithms exist to find the optimal solution.

4.4.1. Solution algorithm

The problem was solved using a standard LP solver. The general steps involved are:

I. Input Data Preparation: Gather necessary data, including:
   - Reliability values for each road segment i in each scenario s ($R_i^s(t)$), calculated as described in Section 4.2.
   - Importance factor for each road segment i (I_i), based on average vehicle usage.
   - Intervention cost for each road segment i (C_i), defined stochastically within limits or based on specific estimations.
   - Total available budget B.
   - Set of road segments E and scenarios S.

II. LP Model Formulation: Construct the mathematical model as defined in equations (10)-(13).

III. Solver Execution: Input the formulated LP model into a dedicated optimization solver. For this study, the CPLEX® Optimizer was utilized within a Python 3.6 environment. CPLEX® employs highly efficient algorithms (such as the Simplex method or interior-point methods) to find the guaranteed optimal solution for LP problems.

IV. Output Results: The solver returns the optimal values for the decision variables x_i, representing the optimal percentage of the intervention budget to allocate to each road segment i to maximize the objective function while respecting the budget constraint. The optimal objective function value Z is also provided.

The sequence of steps involved in the solution algorithm is illustrated in Figure 3.

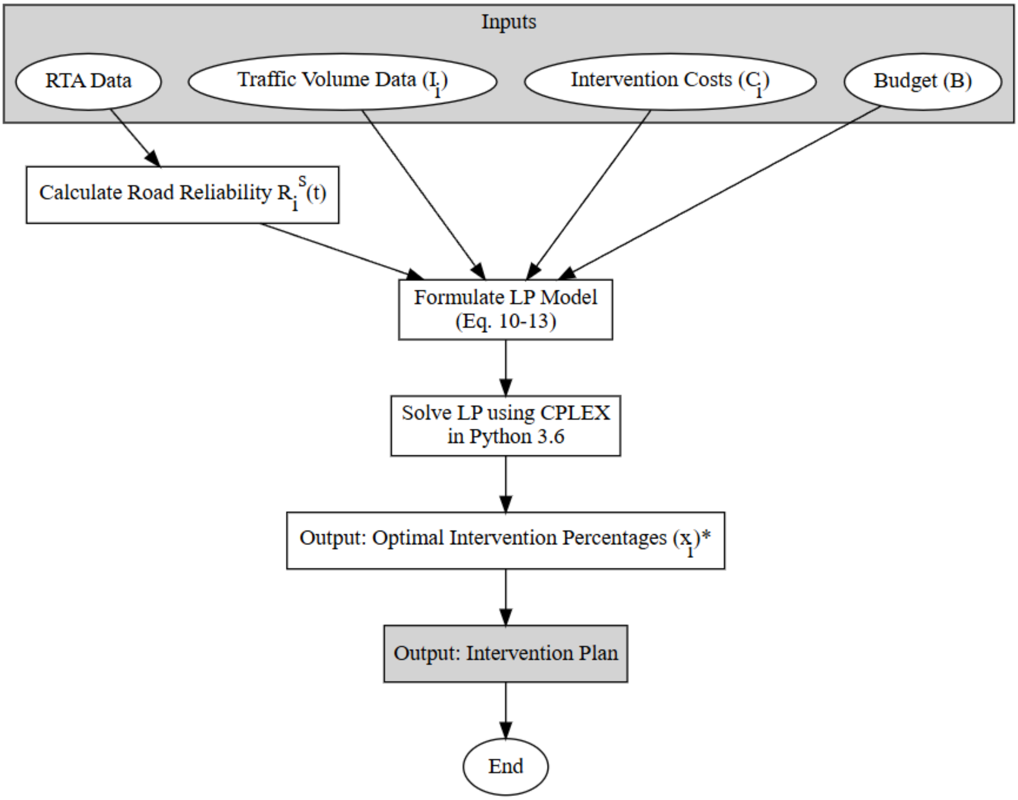

Fig. 3. Flowchart of the Solution Algorithm

4.4.2. Computational details

The LP model was implemented using Python 3.6, interfacing with the CPLEX® optimization solver. Due to the linear nature of the problem and the efficiency of modern solvers like CPLEX, optimal solutions for the case study were obtained rapidly, typically in under one second of computation time on a standard desktop computer. This computational efficiency makes the approach practical for repeated use in planning scenarios. The scientific novelty lies not in the LP solution algorithm itself (which is standard), but in the integration of the RTA-based reliability metric within this specific optimization framework for strategic intervention planning.

5. Results

5.1. Data analysis results

This stage of data analysis has two objectives. Firstly, to know the behavior and consistency of the data with reality and evaluate the fulfillment of the assumption considered in the reliability measurement model used. Secondly, to evaluate the compatibility of the various databases used in this work.

5.1.1. Behavioral analysis of RTA data

As a first step in the analysis of the behavior of the RTA data, we wanted to observe the behavior of accidents throughout the week, to evaluate whether this is related to traffic congestion during peak hours. For this purpose, several box plots were constructed (see Figure 4).

In these plots, similar behaviors can be observed throughout the weekdays, with a marked difference in the behavior during weekends. During the weekdays, there are peaks of accidents during the peak hours of the day, that is, during the morning hours between 6 and 7 a.m. when people travel to their workplaces, the data shows a median of between 7

and 8 RTA per hour. After that, it maintains stability with a sustained frequency and a median between 3 and 5 accidents per hour, until another peak of accidents occurs at midday, between 12 and 13 hours with a median of between 6 and 7 RTA per hour. After midday, it shows a more irregular behavior with a median of between 6 and 10 RTA per hour. The worst peaks are at the time of returning home, with a median of between 9 and 12 RTA per hour, with greater variability between 5 p.m. and 7 p.m. This demonstrates the concordance between peak hours of congestion and peak accident rates on weekdays. On the other hand, Saturdays present an unexpectedly high frequency, with an increasing behavior from 6 am, reaching its highest peak in the midday hours, between 12 and 1 pm. The highest peak on Saturdays ranges between 8 and 12 accidents per hour with a median of 9 accidents. Sundays have a lower frequency of accidents during the day but a higher frequency than other days during the early morning hours. According to this behavior, there is only a marked difference in the behavior of Sundays throughout the data. However, it was decided to use the total information, since Sundays accounted for a total of 9.34% of all data (see Table 2).
The second objective of the data analysis stage is to evaluate compliance with the assumption of the model for measuring the reliability of the transportation system. Under this model, the authors Jovanovic Dragan et al. (2011) propose that the frequency of RTA follows a Poisson distribution or, equivalently, the times between accidents follow an exponential distribution. To validate this assumption, we applied a Kolmogorov-Smirnov goodness-of-fit test to the inter-accident time data for each of the objects of study, i.e. each road. The results of the Kolmogorov-Smirnov test show that the times between each RTA in 101 (87.83%) of the 115 paths follow an exponential distribution with 95% confidence. With these results, for simplification, it is assumed that all roads meet the assumption of the model and follow a distribution of this class. Therefore, the assumption of Jovanovic Dragan et al. (2011) is met with the data under analysis. To show some examples of the behaviors of the times between RTA, several histograms of some roads are shown in Figure 5.

5.1.2. Compatibility between databases

The initial focus of the proposal was to develop an optimization model where two kinds of parameters per road were considered. The first parameter was the reliability of the different roads belonging to the transportation network, considering the interruption generated by traffic accidents in the system. The second parameter was focused on representing the importance of the road, which was achieved by including the utilization factor of each road by counting the number of vehicles transiting it in the network. However, because the counts of vehicles using each road are only available for 61 of the 260 primary roads (see Table 1), it was necessary to section the available data and propose two model approaches, the first one considering this importance parameter, and the second one ignoring this parameter and only taking into account the road reliability parameter.

5.2. Reliability measurement model results

To test the model, accident data for the year 2017 was selected and the necessary data is generated to define the reliability of the primary roadway group working with hourly intervals. The results are shown to be consistent. For the 1-week interval, 7 days x 24 hours were used, and for the 1-year interval, 365 days x 24 hours were used. The Table 4 shows the roads with the highest frequency of accidents (roads 1-10), and those with the lowest frequency of accidents (roads 109-115).
When comparing the results for the reliability of the roads one by one as an independent road for a time segment of 1 week, very similar behaviors are observed to when the reliability of the same roads are compared depending on the different years of the database. This can be observed in Figure 6. The results are shown to be consistent with the reality of the database. Roads with a high frequency of accidents have a reliability close to 0. On the contrary, roads with a low frequency of accidents have a reliability close to 1 in a one-week interval.
A comparison of the reliability of sections at various interval lengths shows that most of the results become closer to a 0 value as the time interval gets longer. This can be explained by the number of accidents that occur; the longer the time interval considered, the higher the frequency of accidents, so the reliability tends to fall rapidly. See Figure 7.

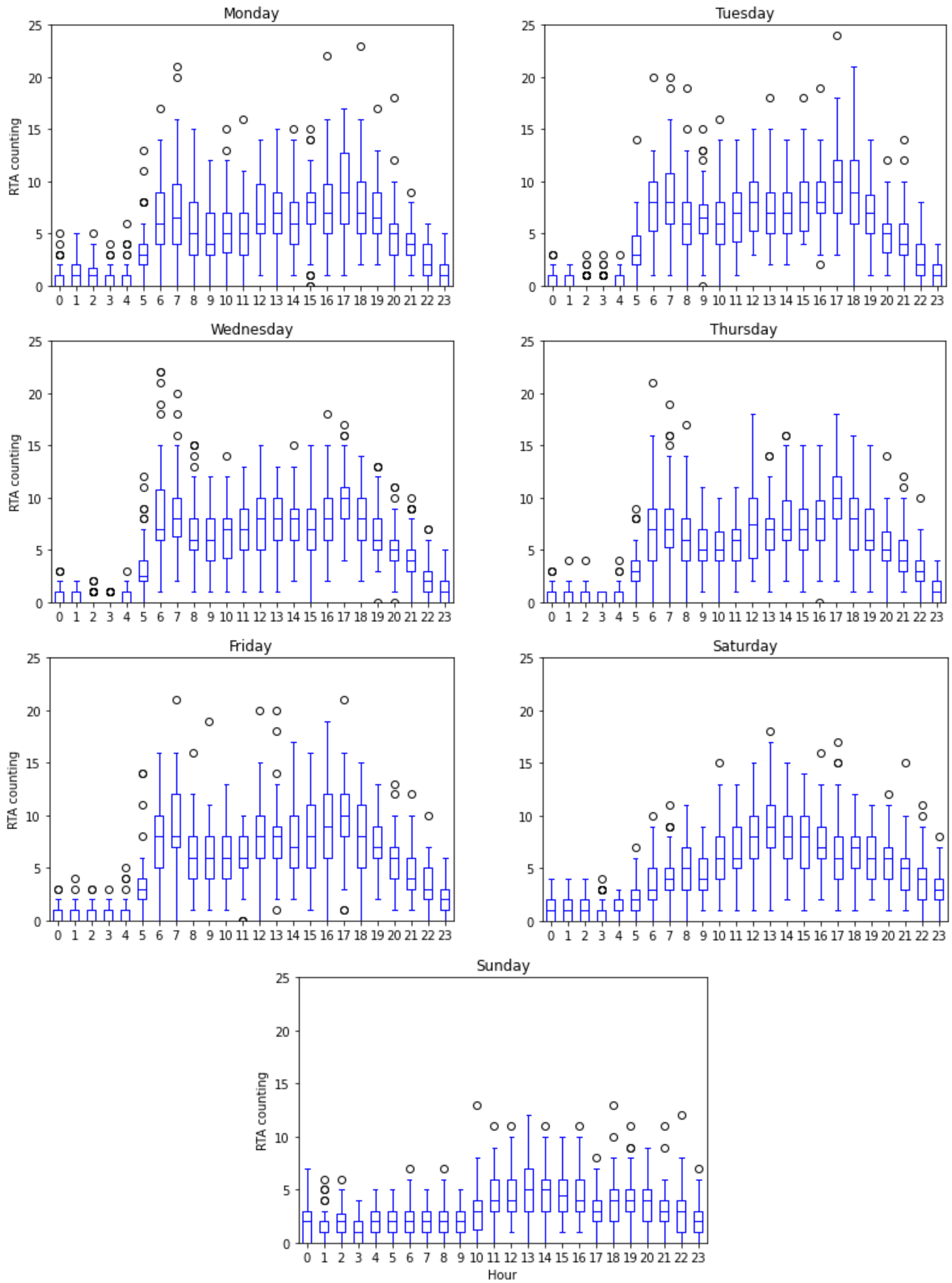

Fig. 4. Box plot of RTA in Medellín (2017-2019) during the hours and days of the week

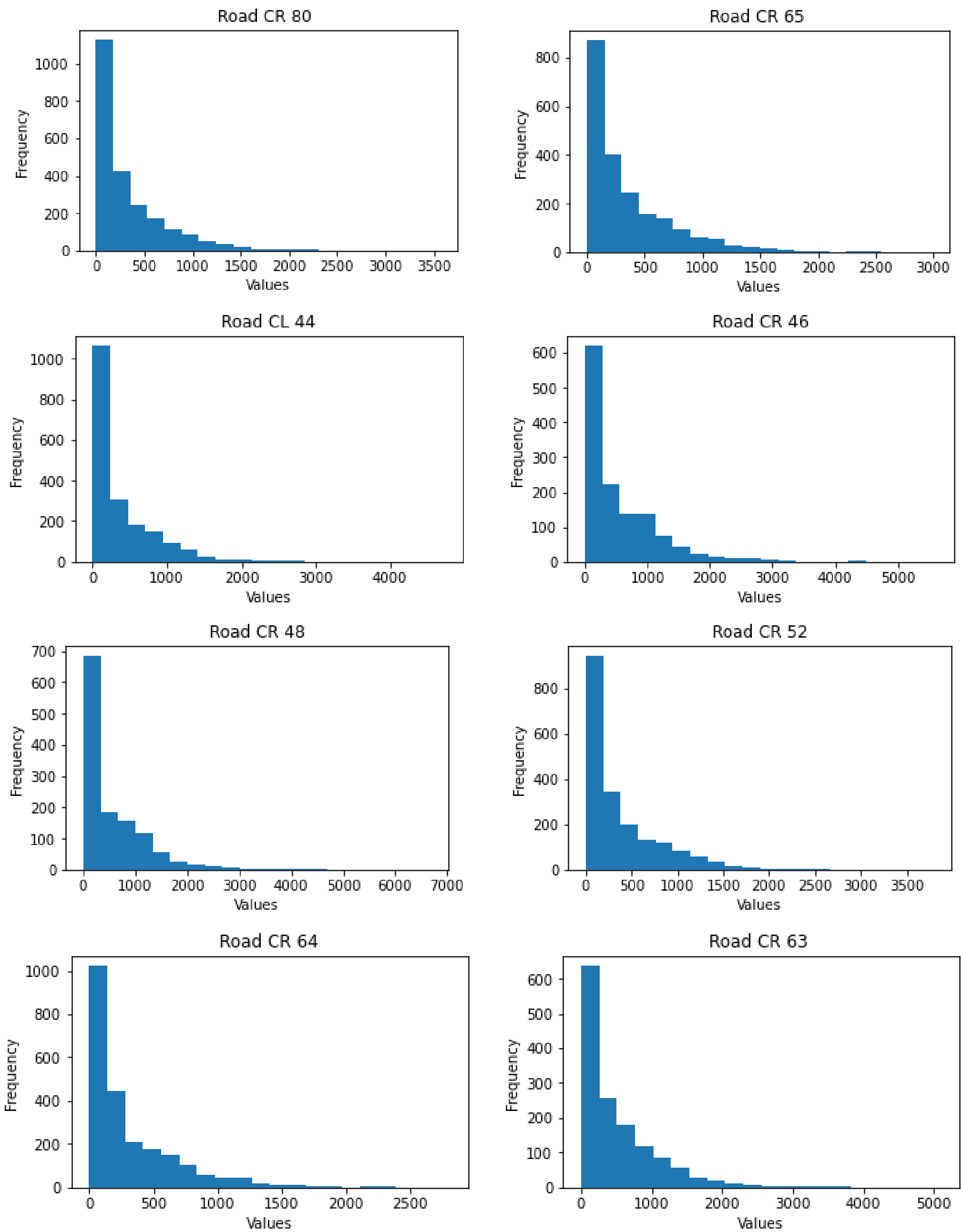

Fig 5. Histograms of the behavior of the times between RTA of some roads

Table 3. Reliability model test summary. Source: Own definition

Road (i)	Name	No. RTA (2017)	$T_{0i}(h)$	λ_i	Reliability 1 week	Reliability 1 year
1	CR 80	1776	4.93	0.20	0.0000000000000016	0.0000000000000000
2	CR 65	1695	5.17	0.19	0.0000000000000076	0.0000000000000000
3	CR 43	1502	5.83	0.17	0.0000000000003090	0.0000000000000000
4	CR 52	1471	5.96	0.17	0.0000000000005599	0.0000000000000000
5	CR 64 C	1420	6.17	0.16	0.0000000000014891	0.0000000000000000
6	CL 44	1404	6.24	0.16	0.0000000000020238	0.0000000000000000
7	CR 63	1291	6.79	0.15	0.0000000000176744	0.0000000000000000
8	CL 10	1026	8.54	0.12	0.0000000028478192	0.0000000000000000
9	CR 48	1014	8.64	0.12	0.0000000035847563	0.0000000000000000
10	CR 46	965	9.08	0.11	0.0000000091743956	0.0000000000000000
...	...	...	...	...	...	...
109	CL 103 A	6	1460.00	0.00	0.8913050935220120	0.0024787521766664
110	CL 18 C	5	1752.00	0.00	0.9085635792245130	0.0067379469990855
111	CR 45 C	5	1752.00	0.00	0.9085635792245130	0.0067379469990855
112	Tv 75	4	2190.00	0.00	0.9261562437967510	0.0183156388887342
113	CR 11 C	3	2920.00	0.00	0.9440895579986100	0.0497870683678639
114	CL 52 B	2	4380.00	0.00	0.9623701178843570	0.1353352832366130
115	CL 72 A	2	4380.00	0.00	0.9623701178843570	0.1353352832366130

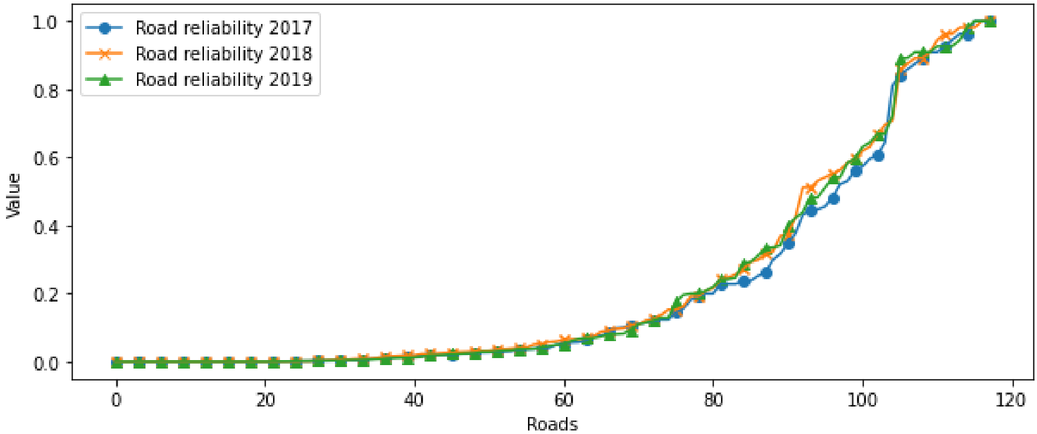

Fig. 6. Reliability of the roads for a time interval of 1 week

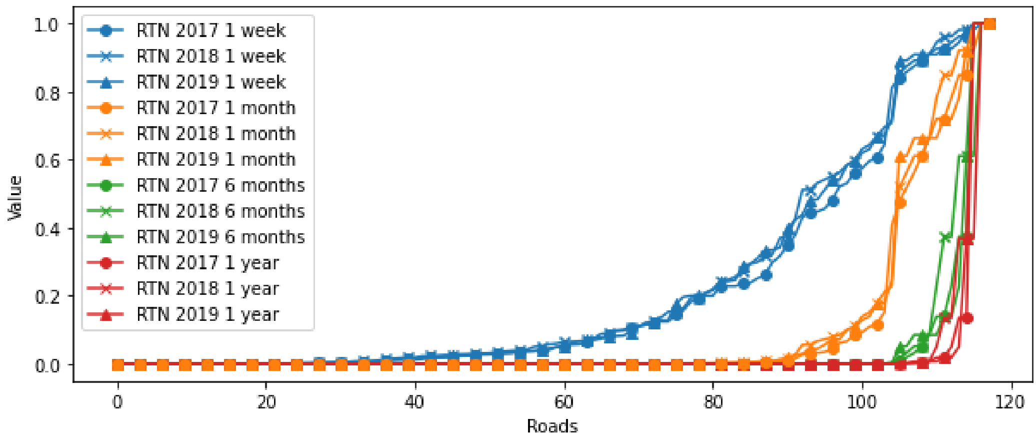

Fig. 7. Reliability of the roads for different time intervals

5.3. Optimization model results

The model was implemented in Python 3.6 and the mathematical model was solved with CPLEX Studio IDE optimizer 20.1.10. The experiments were executed on a 2.4 GHz Ryzen 7 computer with 8 GB of RAM, running on Windows 10 Professional Operating System. The computational requirement of the problem is very low, and the efficiency of both models in solving the problems posed for the case is very high. For both instances, a solution was obtained in less than 1 second.

To develop further experimentation, reliability and cost parameters are considered under different research scenarios. The reliability parameters are evaluated considering the results at an interval of 1 week for each of the real scenarios contemplated (years 2017-2019). Meanwhile, the cost parameter is evaluated under two forms of generation. On the one hand, it was tested using a fixed value of $20,000 dollars, and on the other hand, tests were performed by defining this parameter randomly with values between $10,000 and $25,000 dollars. In many cases, the cost of interventions or road improvements is not known, as these costs are defined after going through stages of analysis and design of changes. One of the purposes of this kind of model is to propose how to make decisions before the intervention, identifying how to invest the budget for road improvement to improve RTN. Therefore, it is useful to test random budget values and evaluate the results.

5.3.1. Model 1 results (with roads importance)

In this case, only 60 primary roads are considered for intervention. To work with this model, a prior procedure of normalization of the values of the importance parameter is used, to bring all the parameters participating in the objective function to close values. If this type of process is not carried out, the solution will be marked by the weight preference of a parameter, and it would not be necessary to use models of this type for decision-making.

When working with a fixed value cost ($C_i =$ \$20,000 dollars) it is evident that the best intervention alternatives are marked by the importance parameter as, despite taking a short time interval of 1 week for experimentation, having normalized this parameter, they still have values much higher than the reliability value of each pathway. For this reason, the optimal decision is defined as intervention alternatives for those roads that show the highest value of the importance parameter.

This can be visualized in Figure 8 where the blue columns are shown as the values of the decision variables. In this case, it is clearly shown that the variables tend to define the intervention in the roads that show the highest value of importance.

When working with random cost values, the changes are shown with respect to the number of roads where interventions are to take place. However, the tendency to select the roads that have the highest value of the importance parameter is preserved. See Figure 9.

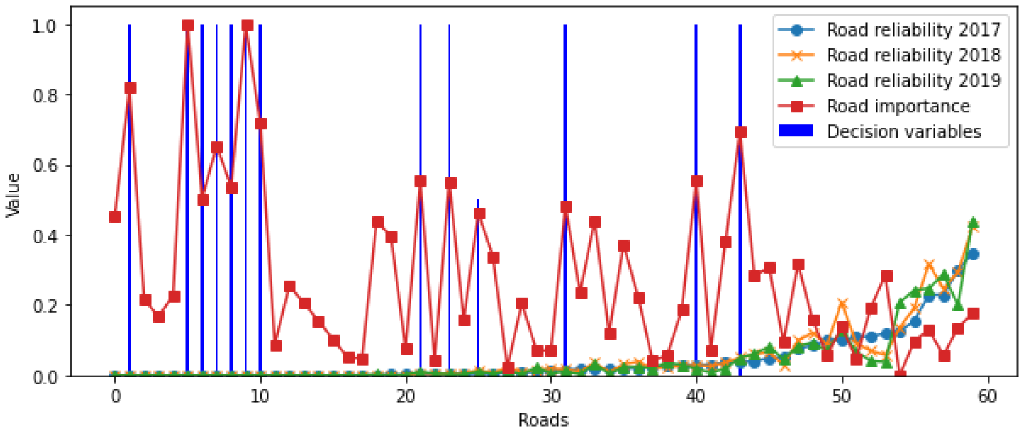

Fig. 8. Optimization model 1 results in cost fixed (Ci = $20.000)

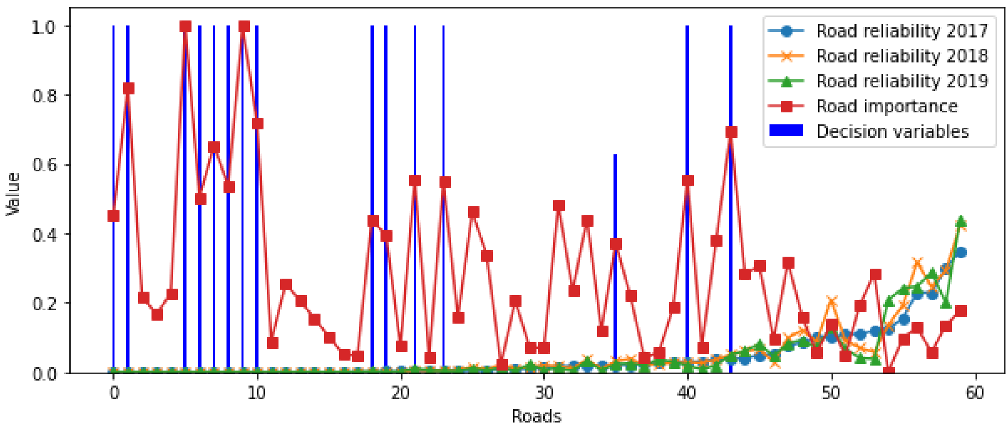

Fig. 9. Optimization model 1 results with random cost value

5.3.2. Model 2 results

For instance, working under this model there are 115 primary roads under study. The results when using a fixed cost of the intervention ($ 20,000) do not yield significant findings, the model simply selects the pathways that present less reliability in the time interval used (1 week). See Figure 10.

The opposite occurs when defining the cost parameter with randomness. Here, the results show a greater dispersion in the decision on the roads where interventions should be done to achieve an increase in the RTN with the available budget.

In this case, the model decides both not necessarily to intervene on the roads with less reliability, and to use all the available budget. This result shows more consonance with what occurs and is often obviated as an alternative. See Figure 11.

6. Discussion

This study introduced an integrated framework combining statistical reliability assessment based on Road Traffic Accidents (RTAs) with a Linear Programming (LP) optimization model for allocating intervention budgets in urban transport networks. The case study in Medellín demonstrated the practical application and efficiency of this approach.

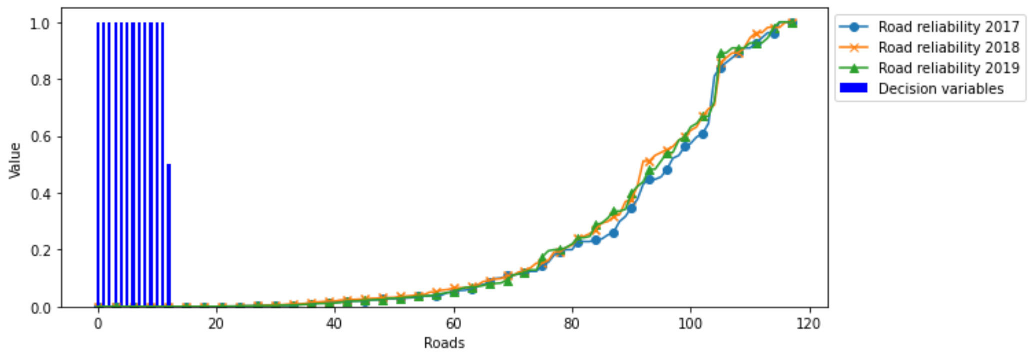

Fig. 10. Optimization model 2 results with fixed cost value

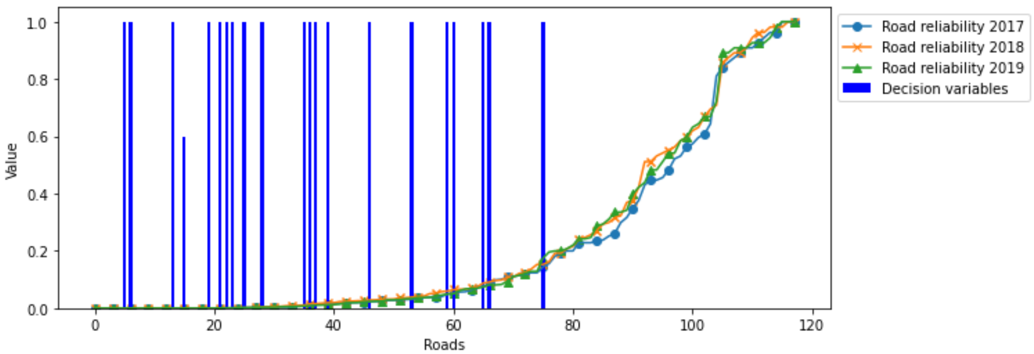

Fig. 11. Optimization model 2 results in random cost value

6.1. Interpretation of findings

The results indicate that the proposed methodology effectively prioritizes road segments for intervention based on their historical reliability (derived from RTA data) and importance (derived from traffic volume). The comparison between the model incorporating road importance (I_i) and the one without showing that explicitly considering traffic volume leads to a more targeted allocation strategy. The importance-weighted model focuses resources on roads that are not only less reliable (higher accident rates relative to exposure) but also carry significant traffic, aligning better with the practical goal of maximizing the impact of limited budgets on overall network performance and safety for the largest number of users. The rapid computation time (<1 second using CPLEX) confirms the suitability of the LP formulation for strategic planning purposes, allowing for easy scenario analysis.

6.2. Contribution to knowledge and practice

The primary contribution of this work lies in the methodological integration of RTA analysis, transport network reliability (RTN) assessment, and optimization for strategic resource allocation. While these fields are well-established, this study provides a clear, data-driven, and computationally efficient framework specifically linking historical accident data to budget allocation decisions aimed at improving network reliability. It operationalizes the concept of reliability, as influenced by RTAs (adapting Jovanović Dragan et al., 2011), into a tangible input for an optimization model.

For practice, this framework offers urban planners and transport authorities a valuable tool for:

– Data-Driven Decision Making: Moving beyond subjective assessments or simple hotspot mapping to prioritize interventions based on quantified reliability and importance.

- Efficient Budget Allocation: Ensuring limited resources are directed towards interventions likely to yield the greatest improvements in safety and network performance.
- Strategic Planning: Providing a repeatable and adaptable methodology for medium-to-long-term planning of road safety investments.

6.3. Advantages and limitations

Advantages:

- Integration: Combines RTA data, reliability concepts, and optimization seamlessly.
- Data-Driven: Bases decisions on historical accident patterns and traffic volumes.
- Targeted Interventions: Incorporating road importance focuses efforts on high-impact segments.
- Computational Efficiency: The LP formulation is solved quickly, facilitating practical use and scenario testing.
- Ease of understanding: The model structure and inputs are relatively straightforward compared to more complex simulation or machine learning approaches.

Limitations:

- Static Approach: The model relies on historical data and does not dynamically simulate traffic flow or predict the precise effect of interventions on future accident rates or network conditions. The effectiveness of an intervention (x_i) is implicitly linked to cost and its impact on the objective function via the reliability term, but the causal mechanisms of accident reduction are not modeled.
- Lack of Simulation Validation: the study does not include microscopic traffic simulation to validate the operational impact of the proposed intervention plan on traffic flow and accident likelihood under dynamic conditions. While simulation is a powerful tool, it represents a significant undertaking requiring detailed network data, calibrated models (traffic flow, driver behavior, accident causation), and substantial computational resources. The focus of this study was on the strategic allocation framework itself, based on historical data analysis and optimization logic. Validating the real-world effectiveness of specific interventions identified by the model would require subsequent empirical study or simulation, which was considered beyond the scope of this initial methodological investigation. Optimization ensures the best allocation according to the model's objective and constraints, relying on the validity of the input reliability metrics derived from historical data.
- Model Assumptions: The reliability model assumes independence between edge failures (accidents). The optimization model assumes intervention costs are known (or can be reasonably estimated) and that the impact on reliability (as captured in the objective function) is appropriately represented. The relationship between the intervention variable x_i and actual reliability improvement is simplified.
- Data Dependency: The quality and granularity of RTA and traffic volume data directly impact on the model's output.
- Scope of Reliability: The current reliability metric is based solely on RTAs. Other factors impacting reliability (e.g., congestion unrelated to accidents, weather, infrastructure failures) are not included.

6.4. Quantifying impact and scenario conditions

The current study demonstrates the allocation strategy but does not quantify the exact resulting increase in network reliability or decrease in accident probability. Such quantification would ideally require follow-up analysis, either through empirical implementation and monitoring or through detailed simulation modeling (as discussed above). The model predicts which allocation maximizes the objective function (a proxy for improving reliability on important roads) under the given budget. The results hold under the conditions represented by the input data (Medellín, 2017-2019 RTA and traffic patterns) and the model's assumptions. Different budget levels (B) or changes in RTA patterns or traffic volumes (I_i) would lead to different optimal allocation plans, which can be explored through sensitivity analysis using the model.

6.5. Future research directions

Future research should prioritize addressing the identified limitations and extending the current framework. Key directions include: (i) Integrating dynamic traffic simulation models to rigorously validate the operational impact of the strategically allocated interventions on traffic flow and accident likelihood. (ii) Developing more comprehensive reliability metrics that incorporate multiple disruption types beyond RTAs, such as recurrent congestion, weather events, and infrastructure failures. (iii) Employing advanced optimization techniques, including stochastic and robust optimization, to more explicitly handle the inherent uncertainties associated with intervention costs, RTA prediction, and intervention effectiveness. (iv) Conducting empirical studies, such as before-and-after analyses, to measure the real-world impact of interventions implemented based on the model's recommendations. (v) Extending and validating the framework in diverse urban contexts worldwide to assess its generalizability and adaptability.

7. Conclusions

This study addressed the critical challenge of enhancing urban transport network reliability, frequently compromised by road traffic accidents (RTAs), through the development and application of an integrated analytical framework. We successfully combined a statistical assessment of network reliability, derived from historical RTA data using an adaptation of the model by Jovanović Dragan et al. (2011), with a linear programming (LP) optimization model designed for the strategic allocation of intervention budgets.

The practical applicability and efficiency of this integrated methodology were demonstrated via a case study in Medellín, Colombia, a city characterized by high traffic congestion and RTA rates. Key findings revealed that the LP model provides optimal allocation solutions rapidly, confirming its suitability for planning purposes. Furthermore, the results underscored the significant benefit of incorporating a road importance factor (based on traffic volume) into the optimization objective; this led to more targeted investment strategies that prioritize interventions on road segments exhibiting both low reliability (high accident impact) and high usage, aligning resource allocation more closely with practical goals of maximizing network-wide safety and performance improvements.

The primary contribution of this research lies in its methodological integration, offering a transparent, data-driven, and computationally efficient tool for urban planners and transport authorities. This framework moves beyond traditional RTA hotspot analysis by explicitly linking accident data to network reliability and optimizing intervention budgets based on both risk and road importance. It provides actionable insights for strategic decision-making aimed at mitigating RTAs and enhancing overall urban mobility.

While the proposed framework offers significant advantages, key limitations should be acknowledged, including the static nature of the model based on historical data and the assumptions inherent in the reliability and optimization formulations. Notably, as discussed, this study did not incorporate dynamic traffic simulation to validate the operational impacts of the proposed interventions, representing an important avenue for future work.

Building on this research, future studies should focus on several key areas. Firstly, validating the effectiveness of the strategically allocated interventions through detailed microscopic traffic simulation or empirical before-and-after studies is crucial. Secondly, enhancing the reliability model to incorporate other sources of network disruption (e.g., congestion, weather events, infrastructure failures) would provide a more comprehensive assessment. Thirdly, exploring advanced optimization techniques, such as stochastic or robust optimization, could better address uncertainties inherent in RTA occurrence, intervention costs, and effectiveness. Finally, applying and comparing the framework across diverse urban contexts globally would further establish its robustness and generalizability. This integrated approach holds considerable potential for improving the safety, reliability, and efficiency of urban transportation systems worldwide.

Acknowledgment

This research was financially supported by the Instituto Tecnológico Metropolitano through project No. P20239.

References

1. Akopov, A.S., Beklaryan, L.A, & Beklaryan, A.L. (2021). Simulation-Based Optimisation for Autonomous Transportation Systems Using a Parallel Real-Coded Genetic Algorithm with Scalable Nonuniform Mutation. *Cybernetics and Information Technologies*, 21(3), 127–144. https://doi.org/10.2478/cait-2021-0034

2. Alcadía de Medellín. (2020). Open Data Medellín. https://geomedellin-m-medellin.opendata.arcgis.com/
3. Area Metropolitana de Medellín. (2017). ENCUESTA ORIGEN DESTINO. https://www.metropol.gov.co/observatorio/Paginas/encuestaorigendestino.aspx
4. Bauer, M., Okraszewska, R., & Richter, M. (2021). Analysis of the causes and effects of cyclist-pedestrian accidents in biggest Polish cities. *Archives of Transport*, 58(2), 115–135. https://doi.org/10.5604/01.3001.0014.8970
5. Bellman, R. (1957). Dynamic Programming. Princeton University Press.
6. Bimpou, K., & Ferguson, N. S. (2020). Dynamic accessibility: Incorporating day-to-day travel time reliability into accessibility measurement. *Journal of Transport Geography*, 89, 102892. https://doi.org/10.1016/j.jtrangeo.2020.102892
7. Briz-Redón, Á., Mateu, J., & Montes, F. (2021). Modeling accident risk at the road level through zero-inflated negative binomial models: A case study of multiple road networks. *Spatial Statistics*, 43, 100503. https://doi.org/10.1016/j.spasta.2021.100503
8. Castañeda, C. P., & Villegas, J. G. (2017). Analyzing the response to traffic accidents in Medellín, Colombia, with facility location models. *IATSS Research*, 41(1), 47–56. https://doi.org/10.1016/j.iatssr.2016.09.002
9. DANE. (2019). Resultados Censo Nacional de Población y Vivienda 2018 (National population census). https://www.dane.gov.co/index.php/servicios-al-ciudadano/60-espanol/demograficas/censos
10. Dantzig, G. B. (1957). Discrete-Variable Extremum Problems. *Operations Research*, 5(2), 266–277. https://doi.org/10.1287/opre.5.2.266
11. Figueira, A. da C., Pitombo, C. S., de Oliveira, P. T. M. e. S., & Larocca, A. P. C. (2017). Identification of rules induced through decision tree algorithm for detection of traffic accidents with victims: A study case from Brazil. *Case Studies on Transport Policy*, 5(2), 200–207. https://doi.org/10.1016/j.cstp.2017.02.004
12. Geneva: World Health Organization. (2018). Global status report on road safety 2018. https://www.who.int/publications/i/item/9789241565684
13. Green, C. P., Heywood, J. S., & Navarro, M. (2016). Traffic accidents and the London congestion charge. *Journal of Public Economics*, 133, 11–22. https://doi.org/10.1016/j.jpubeco.2015.10.005
14. Gutierrez-Osorio, C., & Pedraza, C. (2020). Modern data sources and techniques for analysis and forecast of road accidents: A review. *Journal of Traffic and Transportation Engineering* (English Edition), 7(4), 432–446. https://doi.org/10.1016/j.jtte.2020.05.002
15. INRIX. (2020). 2020 Global Traffic Scorecard. *INRIX Research*. https://inrix.com/scorecard/
16. Jain, S., & Jain, S. S. (2021). Development of Intelligent Transportation System and Its Applications for an Urban Corridor During COVID-19. *Journal of The Institution of Engineers (India): Series B*. https://doi.org/10.1007/s40031-021-00556-y
17. Jose, C., & Vijula Grace, K. S. (2020). Optimization based routing model for the dynamic path planning of emergency vehicles. *Evolutionary Intelligence*. https://doi.org/10.1007/s12065-020-00448-y
18. Jovanović Dragan, D., Bačkalić, T., & Bašić, S. (2011). The application of reliability models in traffic accident frequency analysis. *Safety Science*, 49(8–9), 1246–1251. https://doi.org/10.1016/j.ssci.2011.04.008
19. Kaddoura, I., & Nagel, K. (2018). Using real-world traffic incident data in transport modeling. *Procedia Computer Science*, 130, 880–885. https://doi.org/10.1016/j.procs.2018.04.084
20. Lam, W. H. K., Lo, H. K., & Wong, S. C. (2014). Advances in equilibrium models for analyzing transportation network reliability. *Transportation Research Part B: Methodological*, 66, 1–3. https://doi.org/10.1016/j.trb.2014.05.013
21. Lee, Y., Wei, C. H., & Chao, K. C. (2017). Non-parametric machine learning methods for evaluating the effects of traffic accident duration on freeways. *Archives of Transport*, 43(3), 91–104. https://doi.org/10.5604/01.3001.0010.4228
22. Li, T., Yang, Y., Wang, Y., Chen, C., & Yao, J. (2016). Traffic fatalities prediction based on support vector machine. *Archives of Transport*, 39(3), 21–30. https://doi.org/10.5604/08669546.1225447

23. Martínez-Gabaldón, E., Méndez Martínez, I., & Martínez-Pérez, J. E. (2020). Estimating the impact of the Penalty Point System on road fatalities in Spain. *Transport Policy*, 86, 1–8. https://doi.org/10.1016/j.tranpol.2019.11.003
24. Mitsakou, C., Dimitroulopoulou, S., Heaviside, C., Katsouyanni, K., Samoli, E., Rodopoulou, S., Costa, C., Almendra, R., Santana, P., Dell'Olmo, M. M., Borell, C., Corman, D., Zengarini, N., Deboosere, P., Franke, C., Schweikart, J., Lustigova, M., Spyrou, C., de Hoogh, K., … Vardoulakis, S. (2019). Environmental public health risks in European metropolitan areas within the EURO-HEALTHY project. *Science of the Total Environment*, 658, 1630–1639. https://doi.org/10.1016/j.scitotenv.2018.12.130
25. Mohri, S. S., & Haghshenas, H. (2021). An ambulance location problem for covering inherently rare and random road crashes. *Computers and Industrial Engineering*, 151, 106937. https://doi.org/10.1016/j.cie.2020.106937
26. Muriel-Villegas, J. E., Alvarez-Uribe, K. C., Patiño-Rodríguez, C. E., & Villegas, J. G. (2016). Analysis of transportation networks subject to natural hazards - Insights from a Colombian case. Reliability Engineering and System Safety, 152, 151–165. https://doi.org/10.1016/j.ress.2016.03.006
27. Novikov, A., Shevtsova, A., & Vasilieva, V. (2020). Development of approach to reduce number of accidents caused by drivers. *Transportation Research Procedia*, 50, 491–498. https://doi.org/10.1016/j.trpro.2020.10.090
28. Oskarbski, J. (2017). Automatic road traffic safety management system in urban areas. MATEC Web of Conferences, 122, 03007. https://doi.org/10.1051/matecconf/201712203007
29. Pineda-Jaramillo, J., & Arbeláez-Arenas, Ó. (2021). Modelling road traffic collisions using clustered zones based on Foursquare data in Medellín. *Case Studies on Transport Policy*, 9(2), 958–964. https://doi.org/10.1016/j.cstp.2021.04.016
30. Ravi Sekhar, C., Madhu, E., Kanagadurai, B., & Gangopadhyay, S. (2013). Analysis of travel time reliability of an urban corridor using micro simulation techniques. Current Science, 105(3), 319–329.
31. Rolison, J. J. (2020). Identifying the causes of road traffic collisions: Using police officers' expertise to improve the reporting of contributory factors data. *Accident Analysis and Prevention*, 135, 105390. https://doi.org/10.1016/j.aap.2019.105390
32. Sayyadi, R., & Awasthi, A. (2020). A multi-objective optimization model for sustainable transportation network design. *International Journal of Systems Science: Operations & Logistics*, 7(4), 323-336. https://doi.org/10.1080/23302674.2018.1550929
33. Schoeman, I. M. (2018). Strategies to reduce traffic accident rates in developing countries Lessons learned for assessment and management. *International Journal of Safety and Security Engineering*, 8(1), 98–109. https://doi.org/10.2495/SAFE-V8-N1-98-109
34. Soltani-Sobh, A., Heaslip, K., & El Khoury, J. (2015). Estimation of road network reliability on resiliency: An uncertain based model. *International Journal of Disaster Risk Reduction*, 14, 536–544. https://doi.org/10.1016/j.ijdrr.2015.10.005
35. Soltani-Sobh, A., Heaslip, K., Scarlatos, P., & Kaisar, E. (2016). Reliability based pre-positioning of recovery centers for resilient transportation infrastructure. *International Journal of Disaster Risk Reduction*, 19, 324–333. https://doi.org/10.1016/j.ijdrr.2016.09.004
36. Srinivasan, D., Loo, W. H., & Cheu, R. L. (2003). Traffic incident detection using particle swarm optimization. Proceedings of the 2003 *IEEE Swarm Intelligence Symposium*. SIS'03 (Cat. No.03EX706), Indianapolis, IN, USA, 144-151. https://doi.org/10.1109/SIS.2003.1202260.
37. Sun, C., Pei, X., Hao, J., Wang, Y., Zhang, Z., & Wong, S. C. (2018). Role of road network features in the evaluation of incident impacts on urban traffic mobility. *Transportation Research Part B: Methodological*, 117, 101–116. https://doi.org/10.1016/j.trb.2018.08.013
38. Wajid, S., Nezamuddin, N., & Unnikrishnan, A. (2020). Optimizing Ambulance Locations for Coverage Enhancement of Accident Sites in South Delhi. *Transportation Research Procedia*, 48, 280–289. https://doi.org/10.1016/j.trpro.2020.08.022

39. Wallace, M., Kitson, C., Ormstrup, M., Cherian, J., & Saleh, J. H. (2021). Pedestrian and light transit accidents: An examination of street redesigns in Atlanta and their safety outcomes. Case Studies on Transport Policy, 9(2), 538–554. https://doi.org/10.1016/j.cstp.2021.02.009
40. Wen, H., Wu, J., Duan, Y., Qi, W., & Zhao, S. (2019). A Methodology of Timing Co-Evolutionary Path Optimization for Accident Emergency Rescue Considering Future Environmental Uncertainty. *IEEE Access*, *7*, 131459–131472. https://doi.org/10.1109/ACCESS.2019.2940315