QUALIFYING EXAM

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Automatic Generation of Critical Scenarios for Evaluating Intelligent Control of Autonomous Vehicles in a Simulated Environment

Agenda

- Introduction
- Objectives
- Systematic Review
- Methodology
- Experimental Design
- Results
- Conclusions

BREAKING
TESLA RECALLS NEARLY ALL 2 MILLION OF ITS VEHICLES ON US ROADS
CNN
AP News
A driverless car hits a person crossing against the light in China
BEIJING (AP) — A driverless ride-hailing car in China hit a pedestrian, and people on social media are taking the carmaker's side,...
Financial Times
Self-driving car venture Cruise chief resigns after uproar over accident
Kyle Vogt steps down as company works to 'strengthen public trust' following regulator's ban on its driverless vehicles.
TechCrunch
A Waymo self-driving car killed a
accident
A Waymo robotaxi operating in autonomous
month in San Francisco, according to an inc
jun. de 2023
a small dog last
The Guardian
Tesla Autopilot feature was involved in 13 fatal crashes, US regulator says
US auto-safety regulators said on Friday that their investigation into Tesla's Autopilot had identified at least 13 fatal crashes in which the feature had been...
The New York Times
'Lost Time for No Reason': How Driverless Taxis Are Stressing Cities
In San Francisco and Austin, Texas, where passengers can hail self-driving vehicles, the cars have added to the workloads of city employees.
EL PAÍS English
Study finds self-driving cars are safer than human-driven vehicles
A study published on Tuesday in Nature Communications shows that autonomous vehicles are safer and less likely to be involved in accidents than human-driven...

Origin - Darpa Challenge

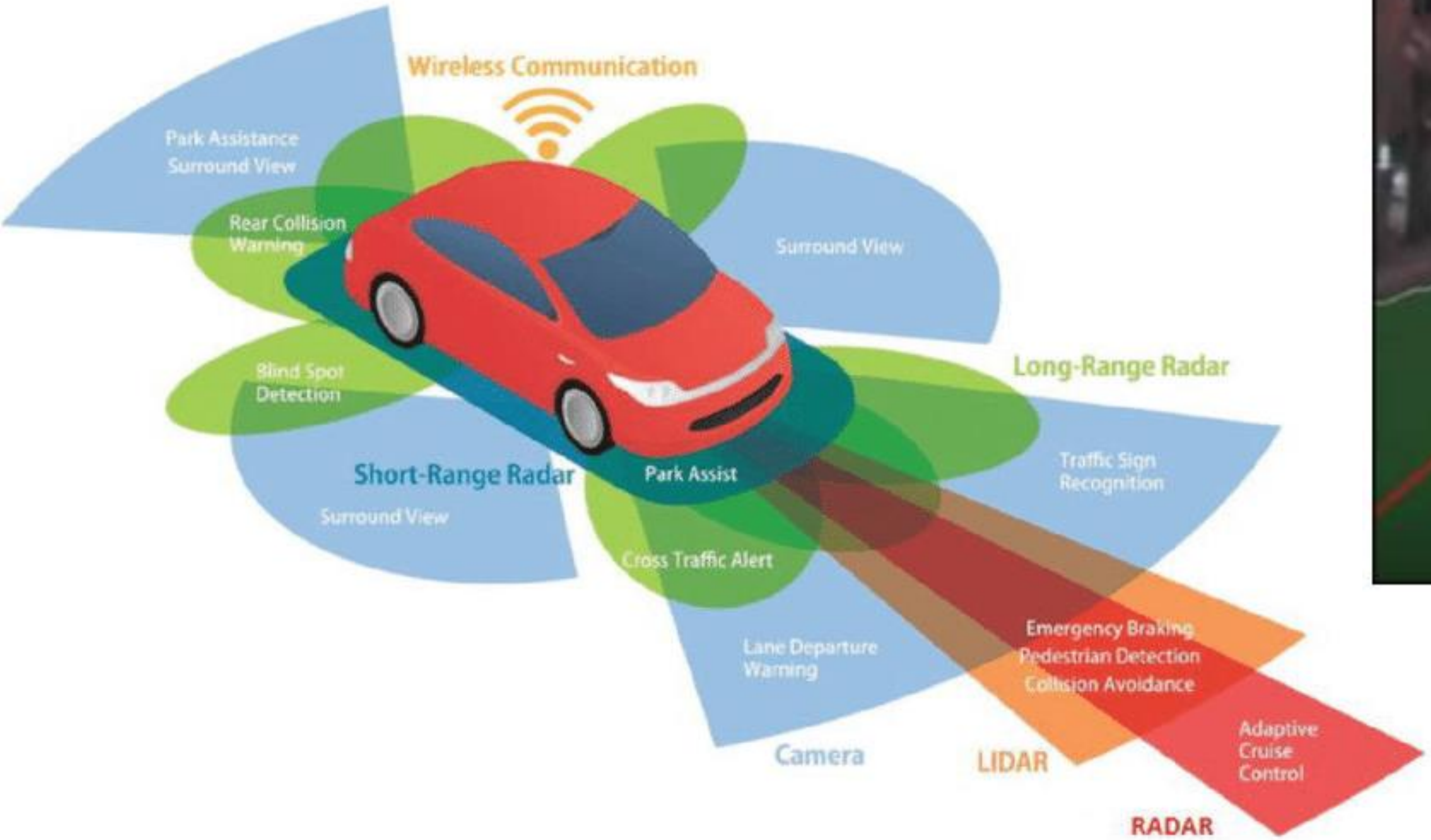
2004

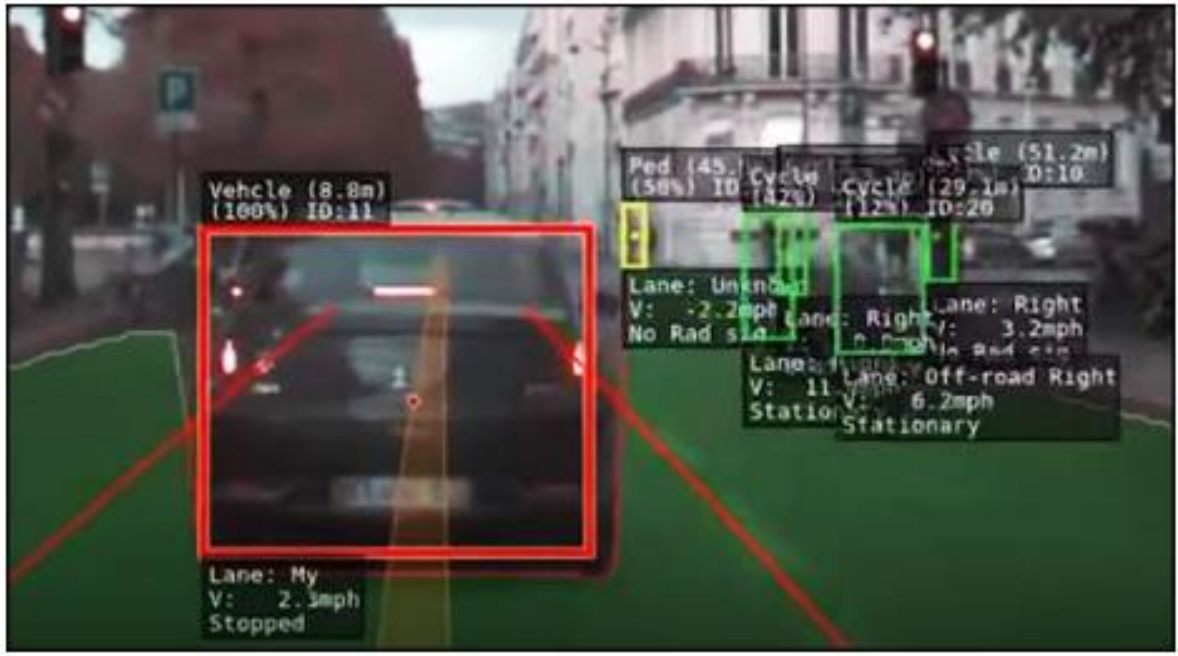
Carnegie Mellon University

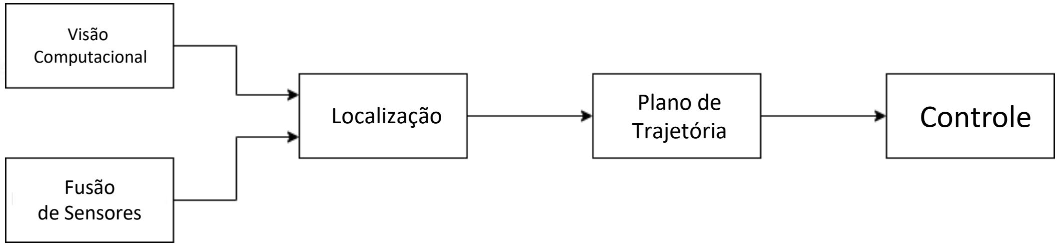
2005

Stanford University

Autonomous Vehicles







[Left image available at the link]()

Right Image: RANJAN, S.; SENTHAMILARASU, S. Applied Deep Learning and Computer Vision for Self-Driving Cars: Build autonomous vehicles using deep neural networks and behavior-cloning techniques. [S.l.]: Packt Publishing Ltd, 2020.

Main Objective

Development of a methodology to identify and automatically generate critical cases (corner cases) with the aim of contributing to future research in the development of more robust vehicle control systems, based on high-risk driving scenarios.

Specific Objectives

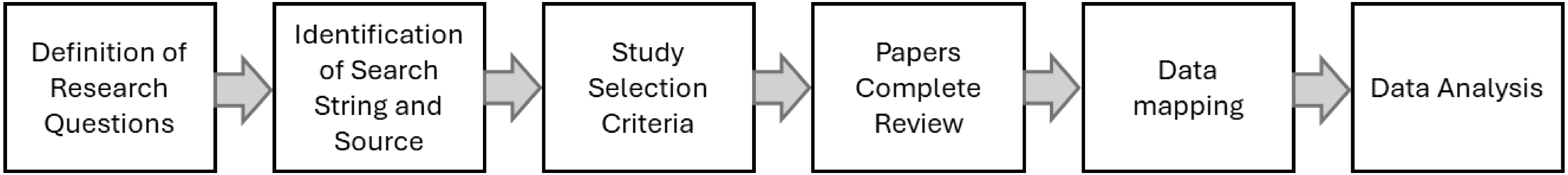
1. Systematically review the State of the Art
2. Organize the literature
3. Implement and test the simulation infrastructure
4. Develop heuristics for selecting parameters related to critical situations
5. Conduct experiments
6. Analyze simulation results
7. Build corner case datasets

STATE OF THE ART

Previous Literature Reviews

	Title	Positive Aspects	Gaps
Mahmud **(2017)**	*Application of proximal surrogate indicators for safety evaluation: A review of recent developments and research needs*	Comprehensive review of safety metrics for autonomous vehicles.	Does not mention corner case generation or testing of critical scenarios.
Westhofen **(2023)**	*Criticality Metrics for Automated Driving: A Review and Suitability Analysis of the State of the Art*		
Rajabli et al. **(2020)**	*Software Verification and Validation of Safe Autonomous Cars: A Systematic Literature Review*	Overview of Verification & Validation and safety standards for autonomous vehicles.	Does not directly address corner case generation; focuses on machine learning overfitting and the need for retraining.
Zhong **(2021)**	*A Survey on Scenario-Based Testing for Automated Driving Systems in High-Fidelity Simulation*	Provides methods for scenario search and performance estimation in simulators.	Not peer-reviewed; lacks reproducibility.
Zhang **(2022)**	*Finding Critical Scenarios for Automated Driving Systems: A Systematic Mapping Study*	Systematic mapping of methods for identifying critical scenarios.	Limited analysis (2017-2020); lacks detailed focus on methods for generating and applying data for safety.
Chib et al. **(2023)**	*Recent advancements in end-to-end autonomous driving using deep learning: A survey*	Covers end-to-end autonomous driving systems and safety enhancement techniques.	Lacks focus on corner case generation or systematic identification.
Ding **(2023)**	*A Survey on Safety-Critical Driving Scenario Generation - A Methodological Approach*	Presents a taxonomy for driving in critical scenarios and corner case generation algorithms.	Not a systematic literature review (SLR); affects comprehensiveness and reproducibility.

Revisão de Literatura – Protocolo

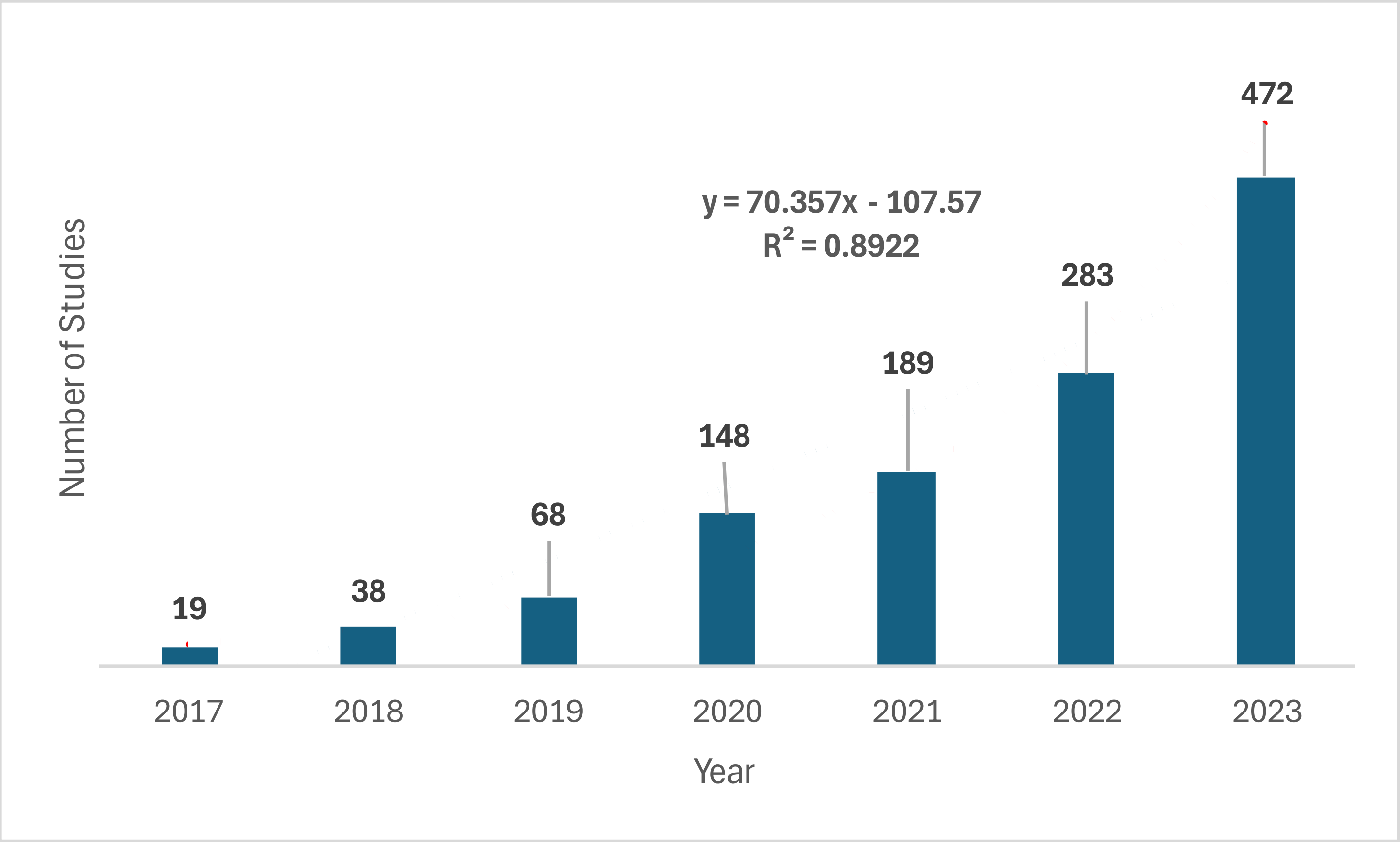


(1) Nascimento, Alexandre Moreira, et al. **"A systematic literature review about the impact of artificial intelligence on autonomous vehicle safety."** *IEEE Transactions on Intelligent Transportation Systems* 21.12 (2019): 4928-4946.

(2) Neto, Antonio V. Silva, et al. **"Safety assurance of artificial intelligence-based systems: A systematic literature review on the state of the art and guidelines for future work."** IEEE Access 10 (2022): 130733-130770.

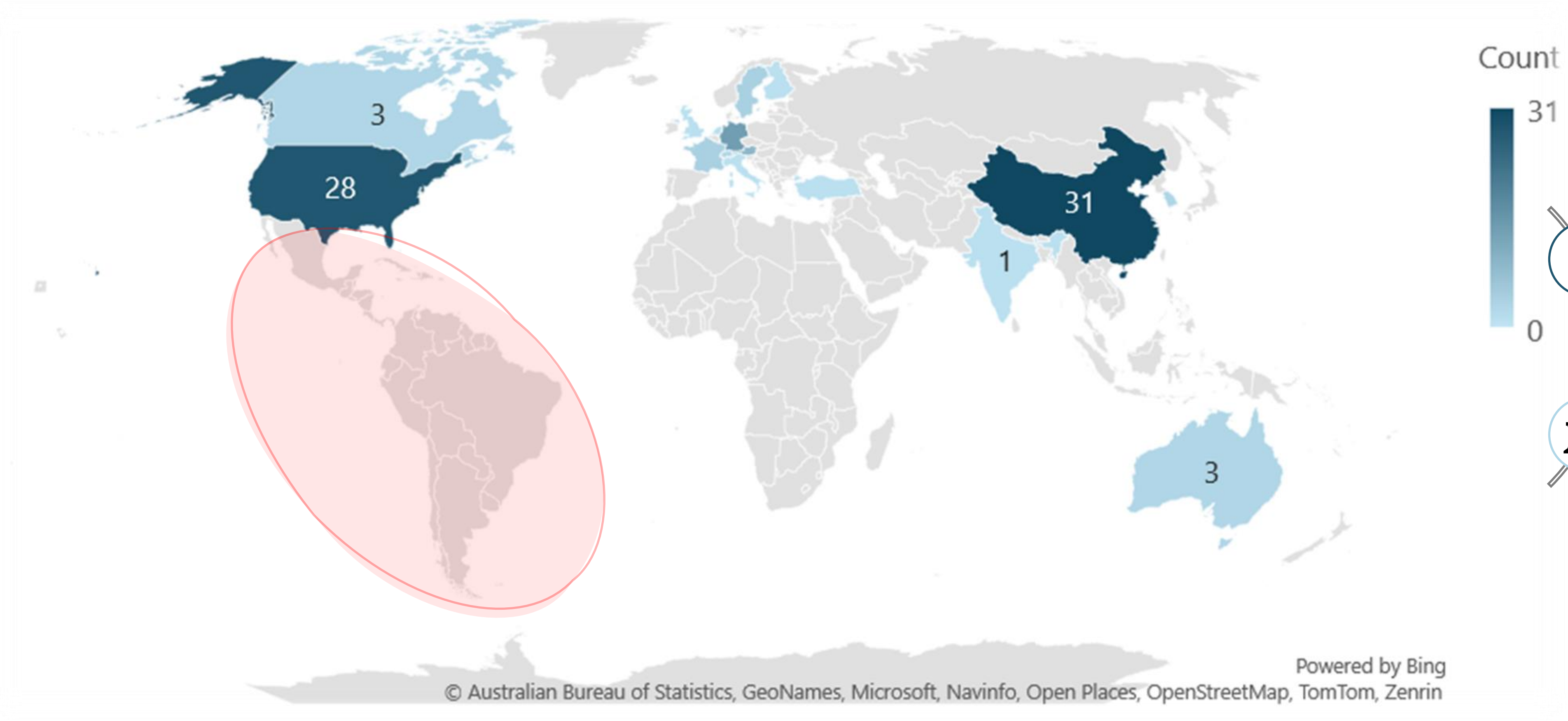
Step	SCOPUS	IEEE	ACM DL	Eng. Vill.	SPRINGER	WOS	Total
RAW	200	46	289	81	1023	34	1673
Abstract Reading	126	46	213	26	15	4	430
Full Paper Reading	55	27	47	11	9	1	150
Final Scope	**40**	**22**	**38**	**4**	**8**	**1**	**113**
Database Effectiveness	20.0%	47.8%	13.1%	4.9%	0.8%	2.9%	6.8%

Evolution of Corner Case Generation Search in Autonomous Vehicles – Google Scholar



Literature Review – Initial Analyses – part (1 / 3)

Geographical Distribution



- Leaders: China / USA
- Europe: Germany / Austria
- Japan: Toyota Research

Literature Review – Initial Analyses – part (2 / 3)

Types of Studies

	Identification	Generation	Hybrid
Focus of Studies	• Methodologies for identifying critical scenarios • Overcoming limitations of traditional testing	• Modeling of Critical Scenarios in a Controlled Manner • Extension of real and simulated data	• Integration of Techniques to Maximize the Identification and Generation of Critical Scenarios
Highlights	• Simulation-based testing • Search algorithms to cover large search spaces	• Frameworks that Balance Safety and Efficiency • Expanding critical scenarios for robust testing of AVs	• Simulation tools covering data gaps • Iterative processes for evaluating multiple scenarios
Challenges / Opportunities	• Validating systems under conditions difficult to replicate in real life • Prioritizing critical scenarios that identify unexpected behaviors	• Ensuring Realism in Generated Scenarios • Scalability for large-scale testing without losing efficiency	• Complexity in integrating different techniques • High computational power required for hybrid processes

Literature Review – Initial Analyses – part (3 / 3)

Conclusions

Key Observations

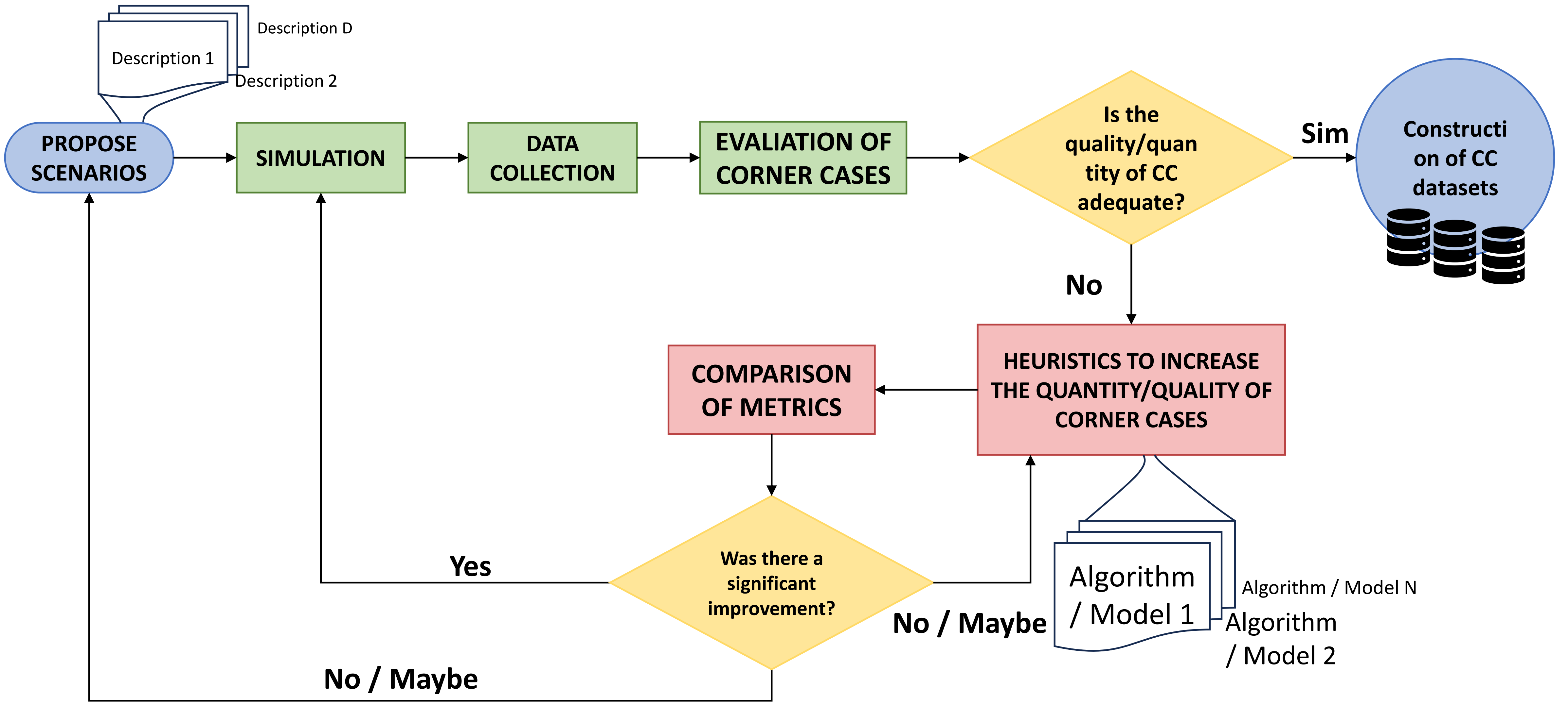
- **Identification-only** techniques are essential to uncover specific weaknesses.
- Data **generation** offers flexibility and extends the limits of testing.
- **Hybrid** methods are more promising for comprehensive and robust evaluation.

Gaps and Promising Directions

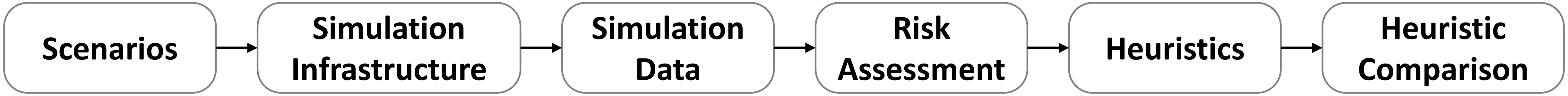
- Increase the use of hybrid approaches.
- Focus on techniques that combine efficiency and accuracy.
- Promote interdisciplinary collaboration to overcome limitations of real-world data. (Sim2Real gap)

METHODOLOGY

Improvement of Data Generation

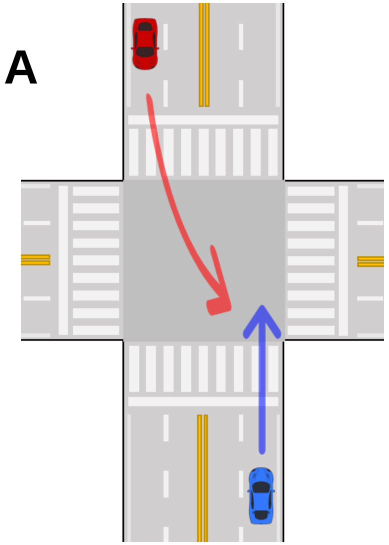


Development Flow

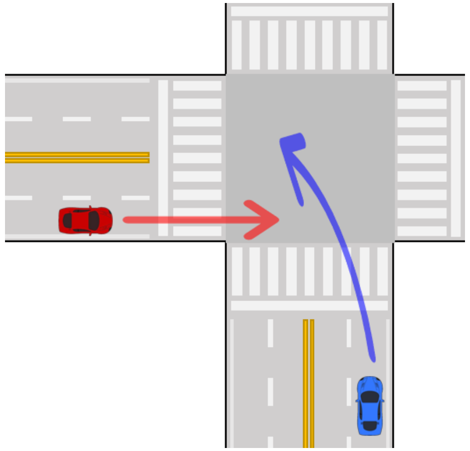


Scenarios – NHTSA (2011-2015)

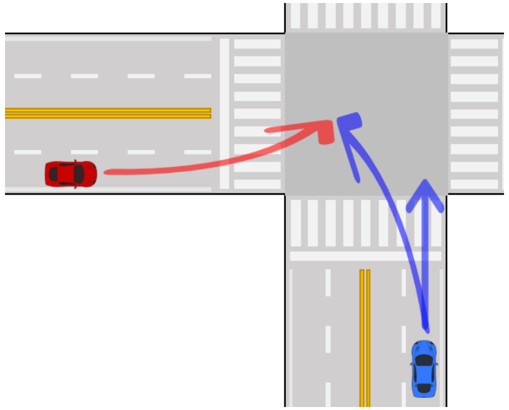
A



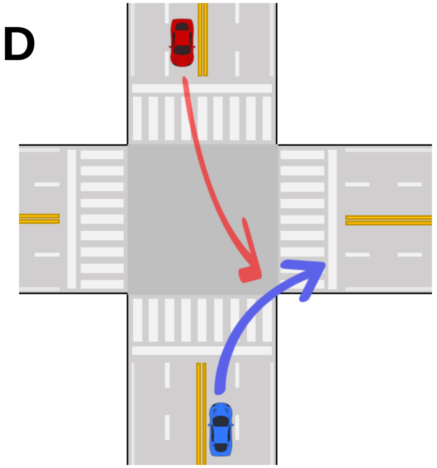
B



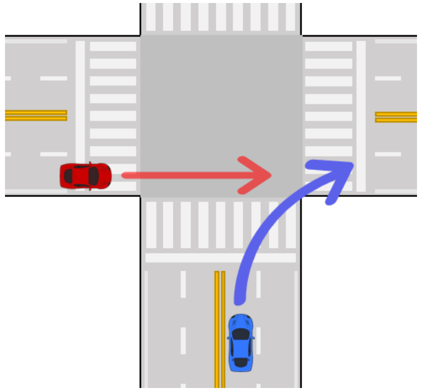
C



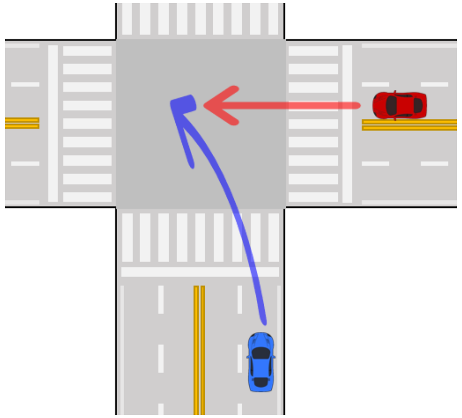
D



E



F



* SWANSON, E. D. et al. Statistics of light-vehicle pre-crash scenarios based on 2011–2015 national crash data. [S.l.], 2019.

Simulation Infrastructure

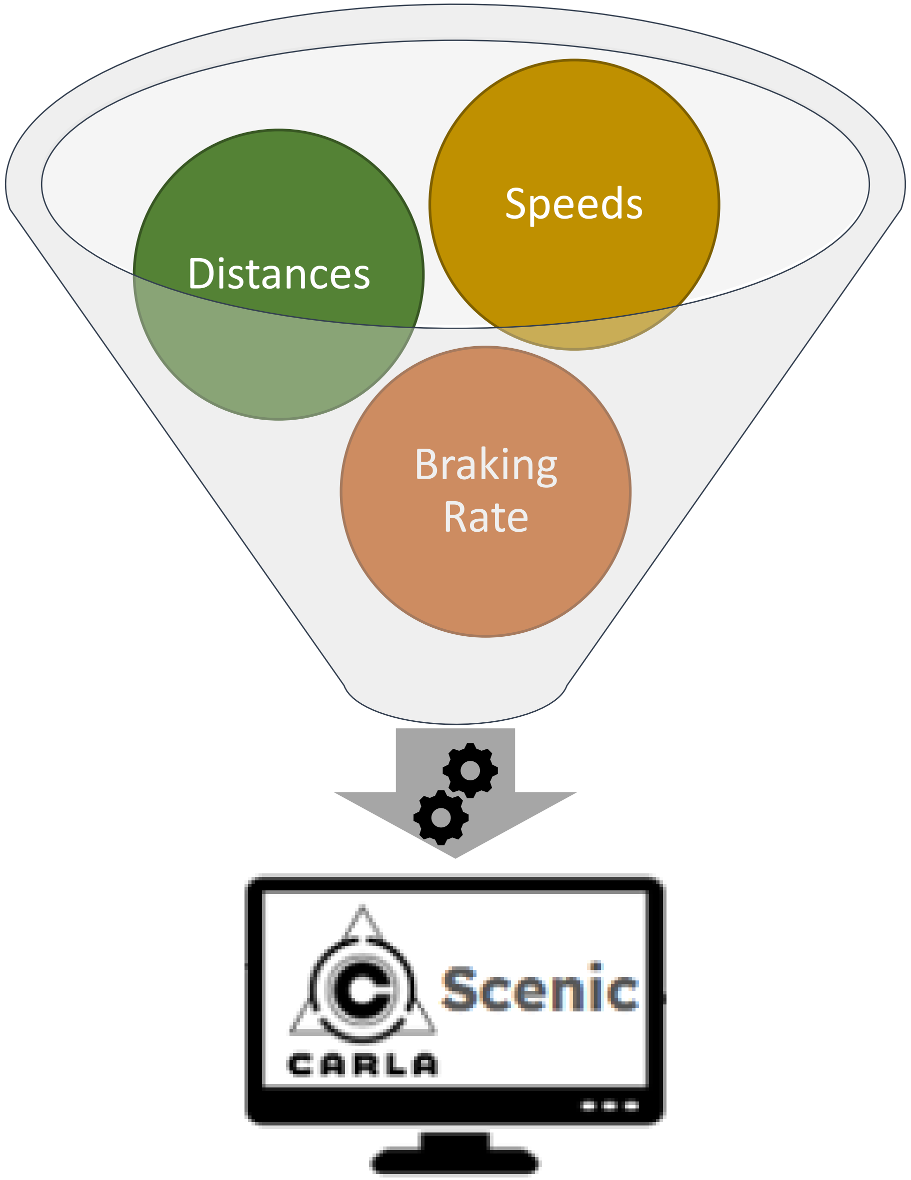
Scenarios → **Simulation Infrastructure** → Simulation Data → Risk Assessment → Heuristics → Heuristic Comparison

Scenic | Description → Search → Simulation

+

- Widely Used
- OPEN-SOURCE
- CARLA
- Realism
- Various Tools

Scenic



Simulation Generation

Scenarios → Simulation Infrastructure → Simulation Data → Risk Assessment → Heuristics → Heuristic Comparison

Risk Metrics

Scenarios → Simulation Infrastructure → Simulation Data → Risk Assessment → Heuristics → Heuristic Comparison

Type	Description	
Event	**Collision Occurance (C)**	(Nascimento, et al., 2021)
Command	Steering Wheel Oscillation	(Kim, et al., 2022)
	Flip Count: Pedal Alternation (Accelerator, Brake)	(Nascimento, et al., 2021); (Kim, et al., 2022)
Dynamic	**Minimum Relative Distance Between Vehicles (MD)**	(Kim, et al., 2022); (Shu, et al. 2021); (Zhu, et al., 2023)
	Relative Speed (Closing Speed) of Vehicles at the MD Point	(Zhu, et al., 2023)
	Time to Collision (TTC) of Vehicles at the MD Point	(Tian, et al., 2022); (Song, et al., 2022); (Shu, et al. 2021)
	Relative Distance Between Vehicles at the Maximum Speed (D_MS) Point	(Kim, et al., 2022)
	Relative Speed (Closing Speed) of Vehicles at the MD Point	(Zhu, et al., 2023)
	Time to Collision of Vehicles at the MS Point (TTC_MS)	(Tian, et al., 2022); (Song, et al., 2022); (Shu, et al. 2021)

METRICS	RANGE	SCORE
C	Collision	10
	No Collision	0
MD	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0
D_MS	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0
TTC_MS	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0

22

F = s(C) + s(DM) + s(D_VM) + s(TTC_VM)

Valid Range: [-1, 22]

Exemplo – Cálculo de Risco

METRICS	RANGE	SCORE
C	Collision	10
	No Collision	0
MD	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0
D_MS	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0
TTC_MS	Range 1	4
	Range 2	3
	Range 3	2
	Range 4	1
	Range 5	0

F = s(C) + s(DM) + s(D_VM) + s(TTC_VM)

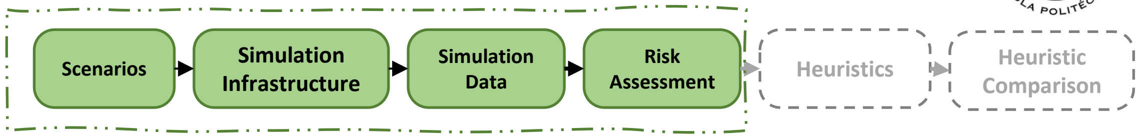
Examples

Score

Score	
12	• **Collision** (10) + Score Combination **MD**, **D_MS**, **TTC_MS - (2)** • **MD** (4) + **D_MS** (4) + **TTC_MS** (4) – **Total**: 12
14	• **Collision** (10) + Score Combination **MD**, **D_MS**, **TTC_MS - (4)**

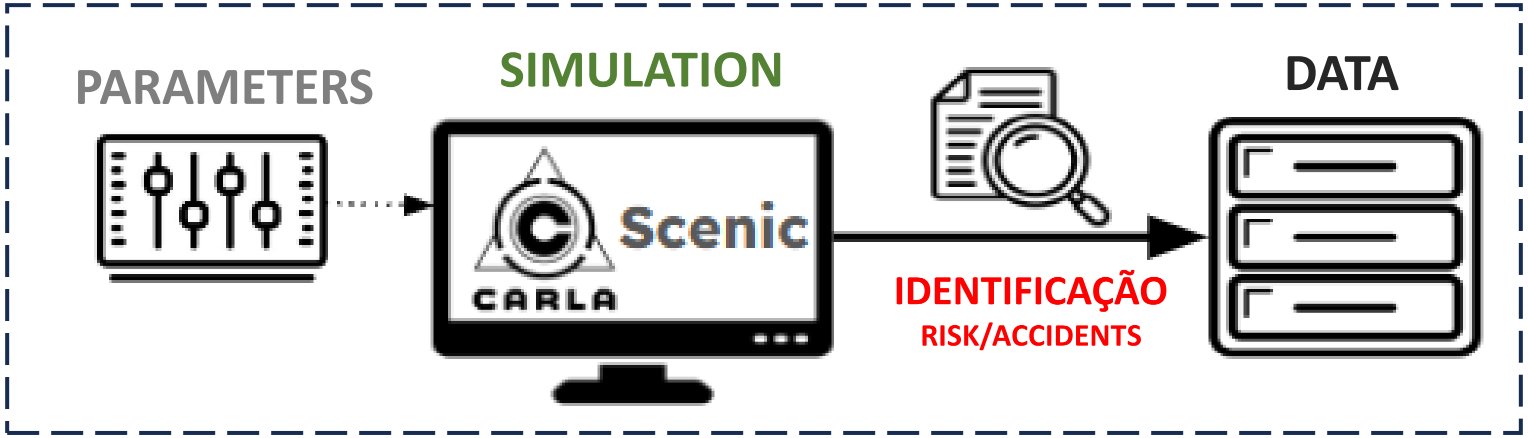
EXPERIMENTAL DESIGN

Simulation Infrastructure

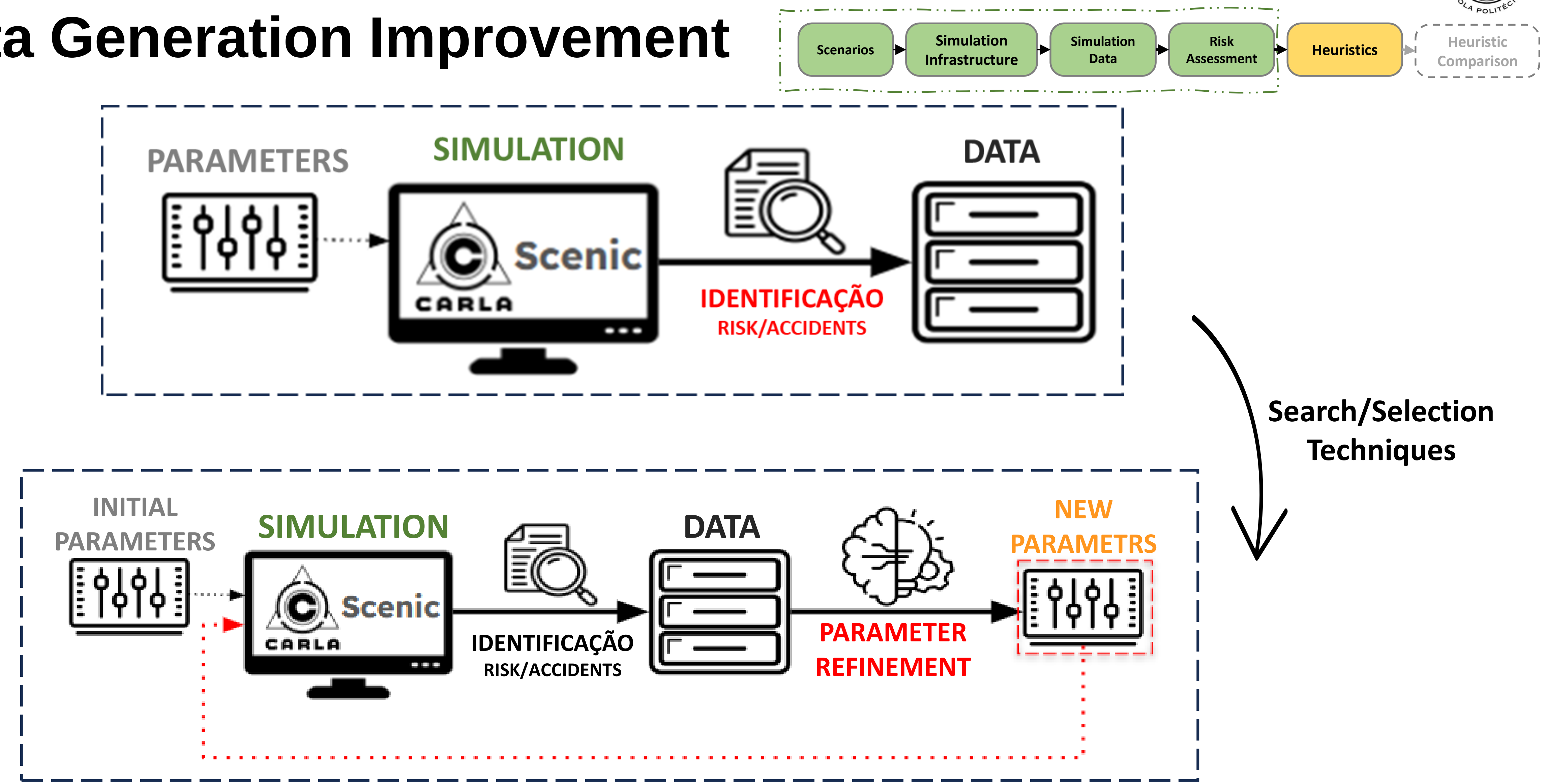


Parâmetros	Tipo	Intervalo Válido
EGO_INIT_DIST	numeric	[0, +∞[
EGO_SPEED	numeric	[5, 80]
EGO_BRAKE	float	[0, 1]
ADV_INIT_DIST	numeric	[0, +∞[
ADV_SPEED	float	[5, 80]
SAFETY_DIST	float	[0, 20]
CRASH_DIST	float	[0, 5]

```
###################################
# CONSTANTES                      #
###################################

MODEL = 'vehicle.lincoln.mkz_2017'

EGO_INIT_DIST = [10, 13] # intervalo da posição inicial do VA
param EGO_SPEED = VerifaiRange(60, 80)
↪ # intervalo da velocidade máxima do VA
param EGO_BRAKE = VerifaiRange(0.5098506134136033, 0.5298506134136033)
↪ # taxa de frenagem do VA

MODEL_ADV = 'vehicle.mercedes.coupe_2020'

ADV_INIT_DIST = [12, 15]
↪ # intervalo da posição inicial do veículo adversário
param ADV_SPEED = VerifaiRange(18, 19)
↪ # intervalo da velocidade máxima do veículo adversário

param SAFETY_DIST = VerifaiRange(9, 10) # distância considerada segura
```

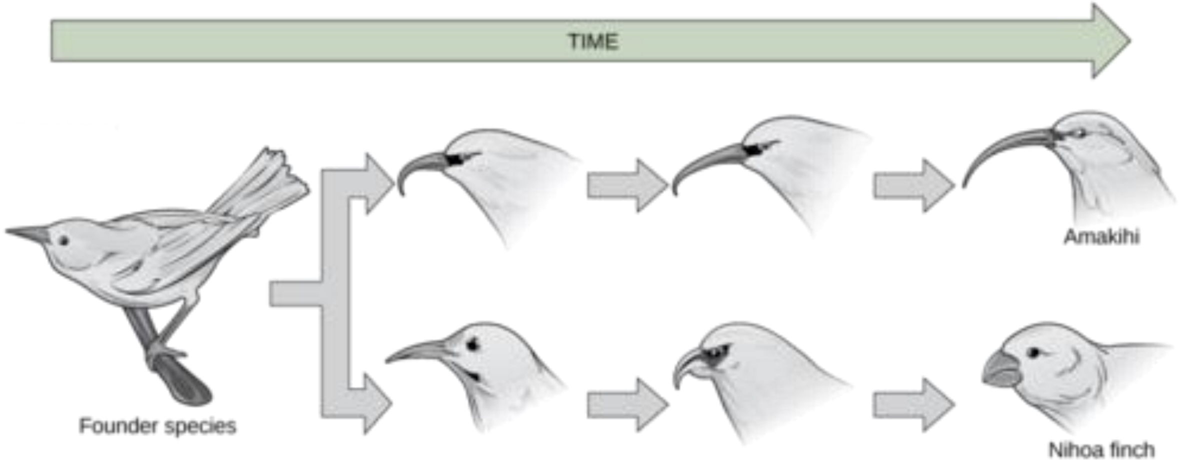


Data Generation Improvement

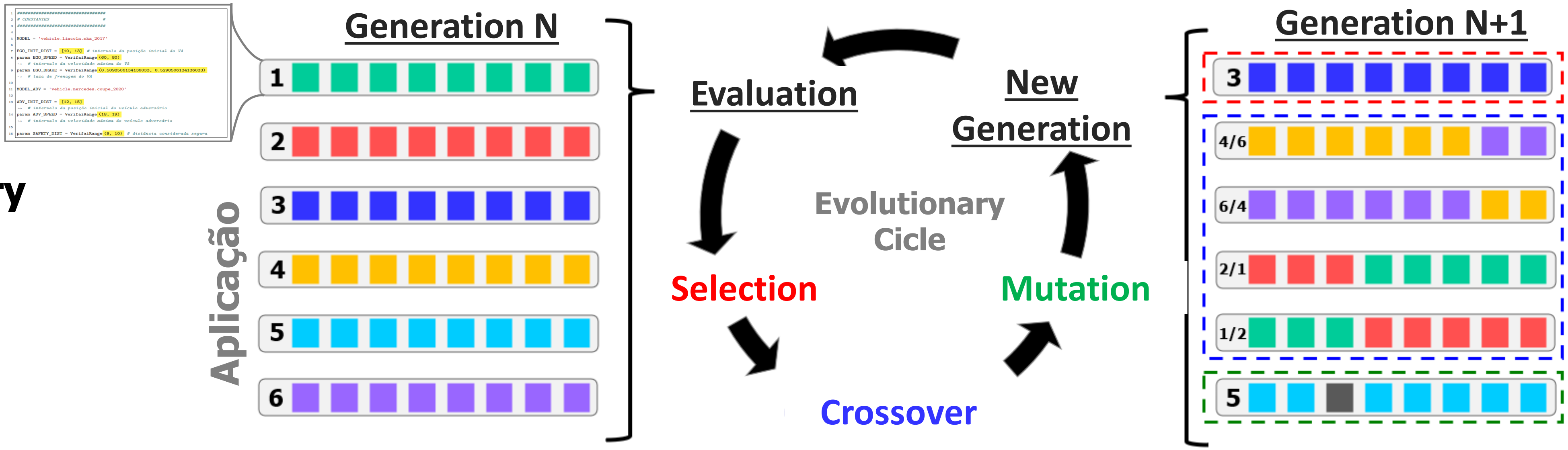


Parameter Refinement – Genetic Algorithm

Biological Evolution

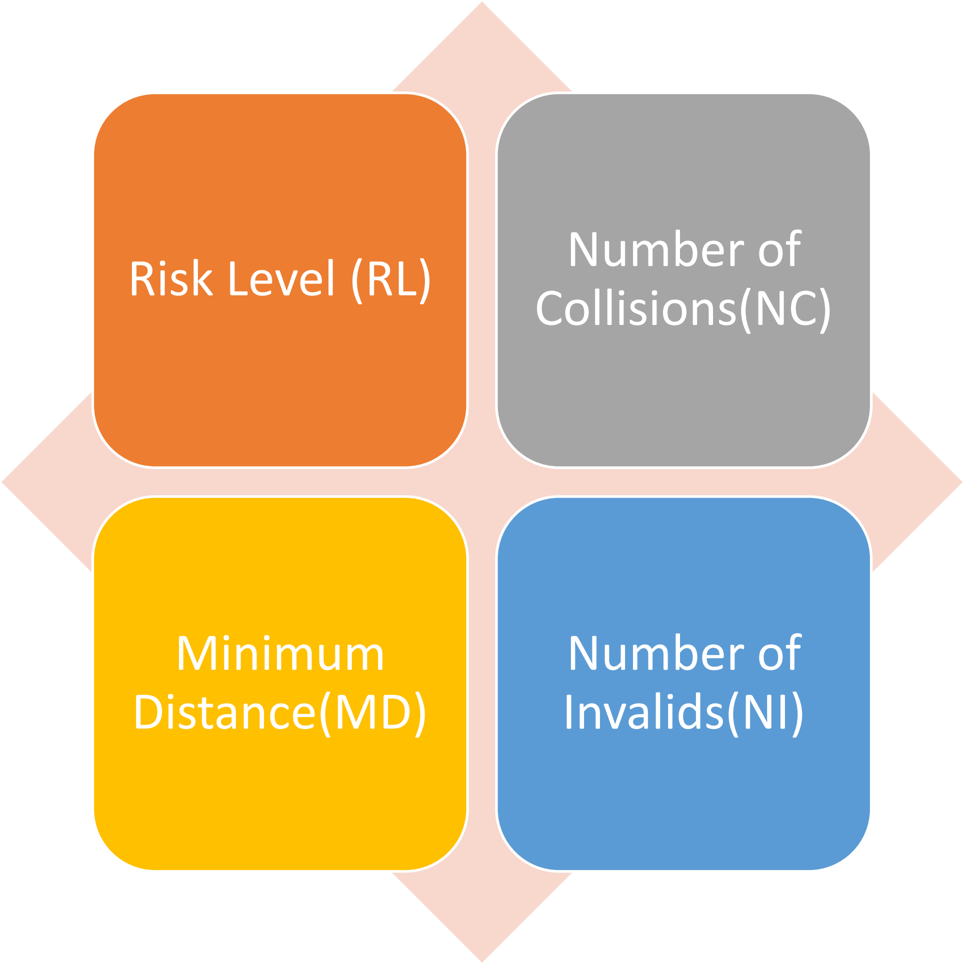


Evolutionary Algorithm



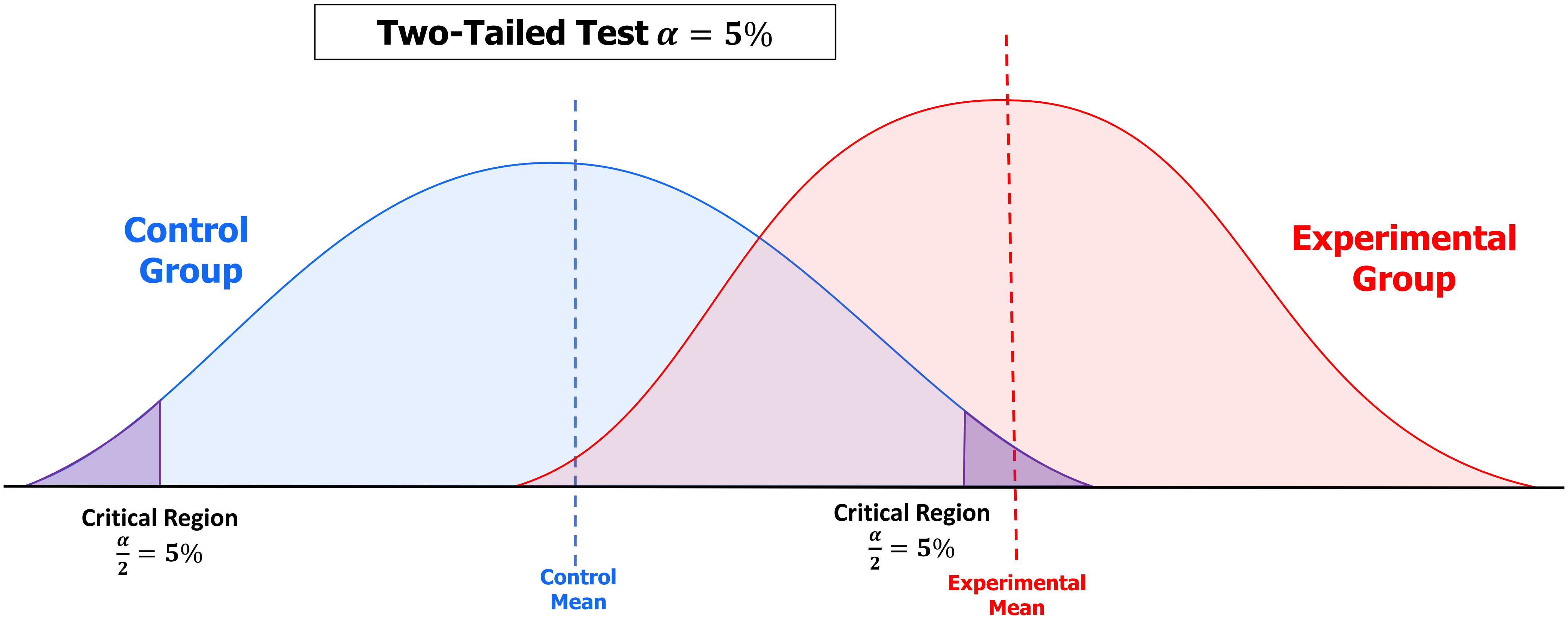
Heuristic Evaluation Metrics

Scenarios → Simulation Infrastructure → Simulation Data → Risk Assessment → Heuristics → **Heuristic Comparison**

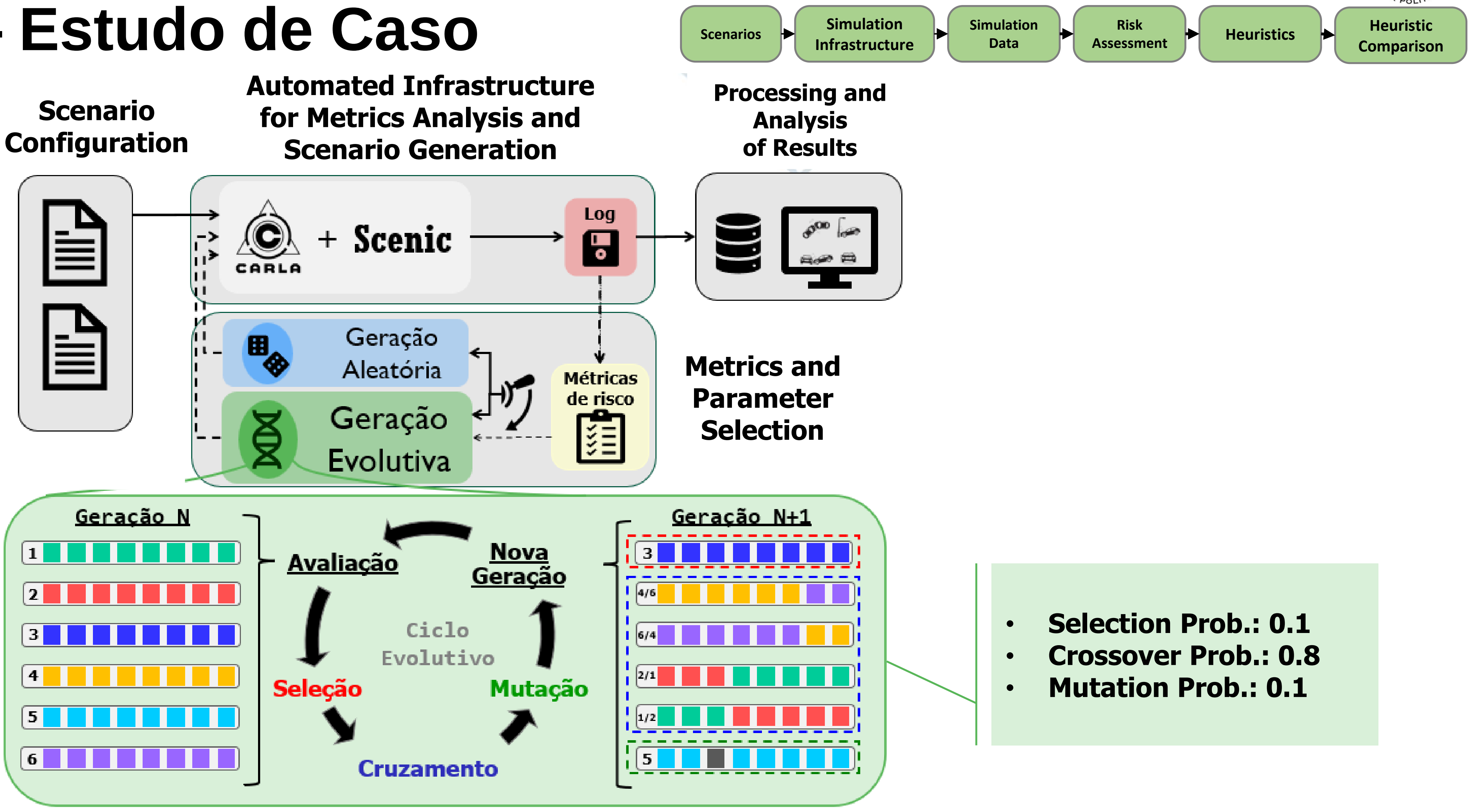


Experimental Protocol – Heuristic Comparison

Scenarios → Simulation Infrastructure → Simulation Data → Risk Assessment → Heuristics → Heuristic Comparison



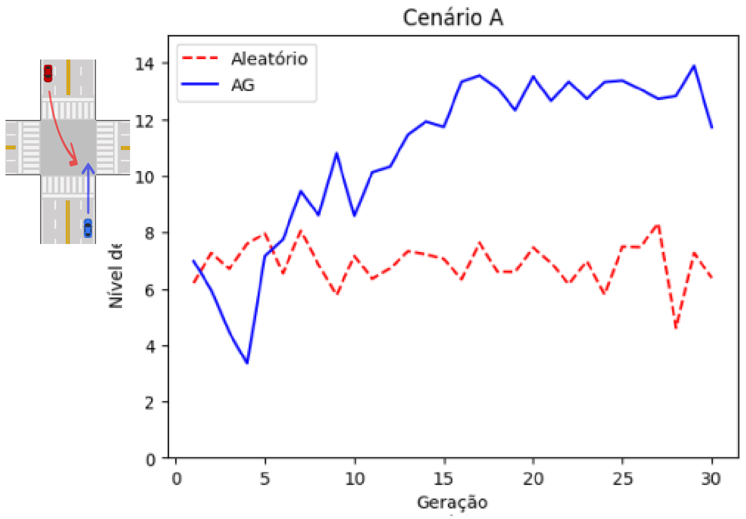
Modelo – Estudo de Caso

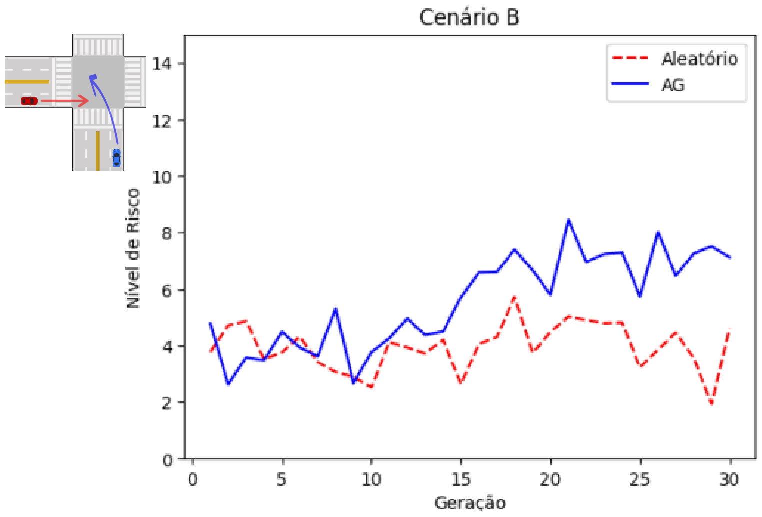


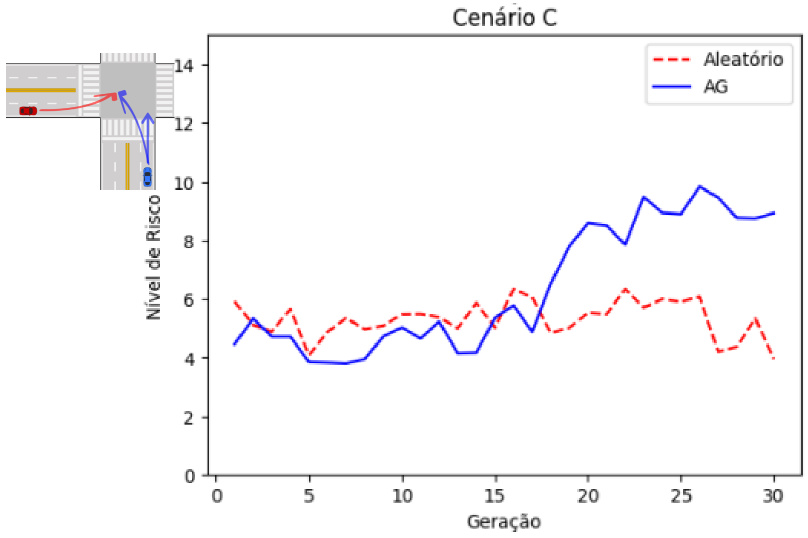
- Selection Prob.: 0.1
- Crossover Prob.: 0.8
- Mutation Prob.: 0.1

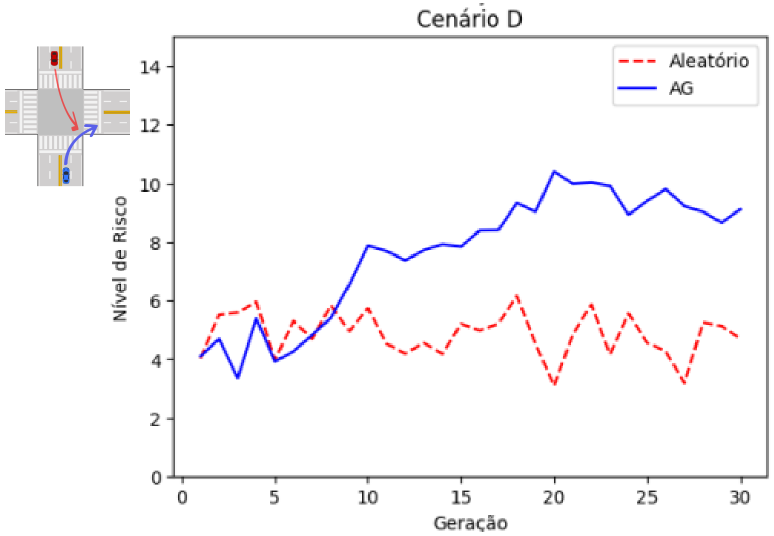
RESULTS

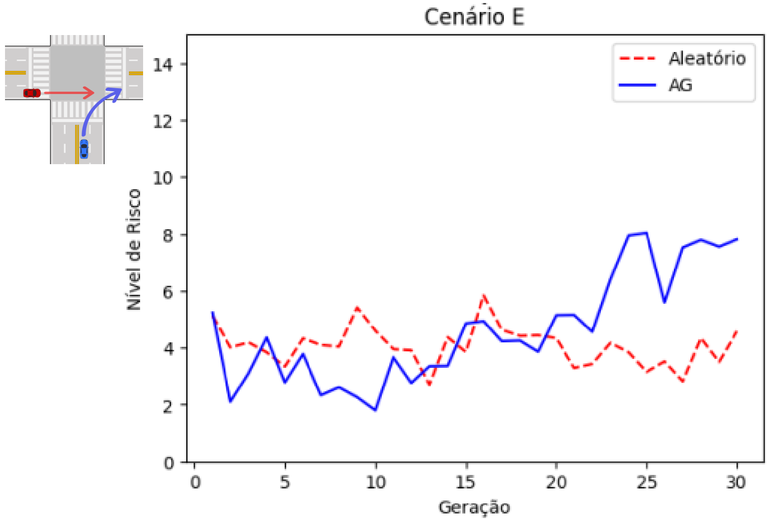
Results – Risk Level (RL) – parte (1 / 2)

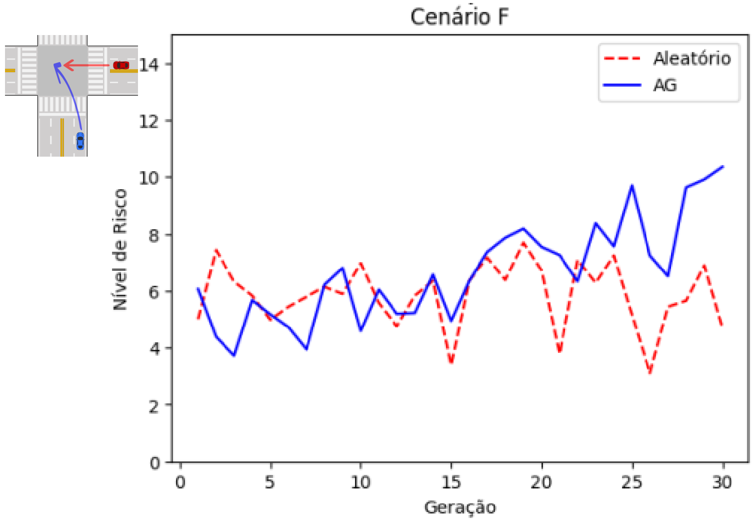








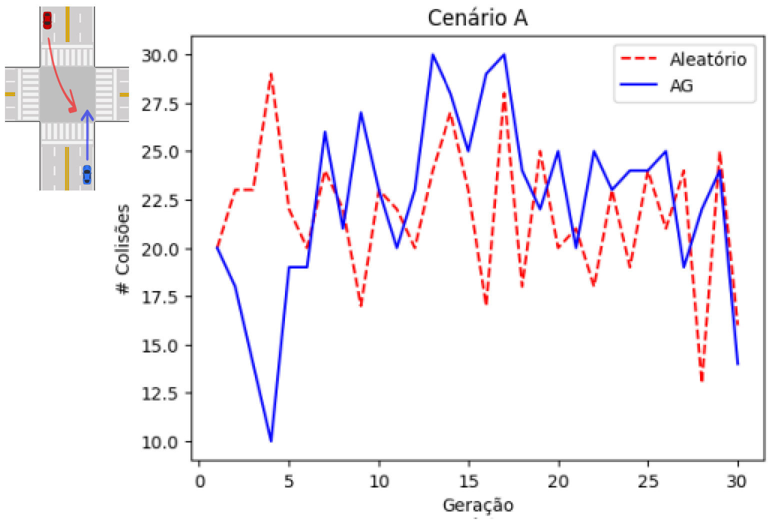


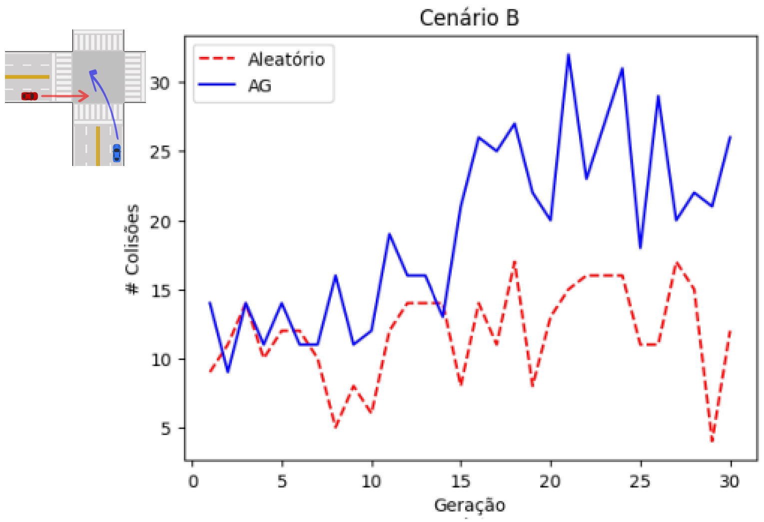


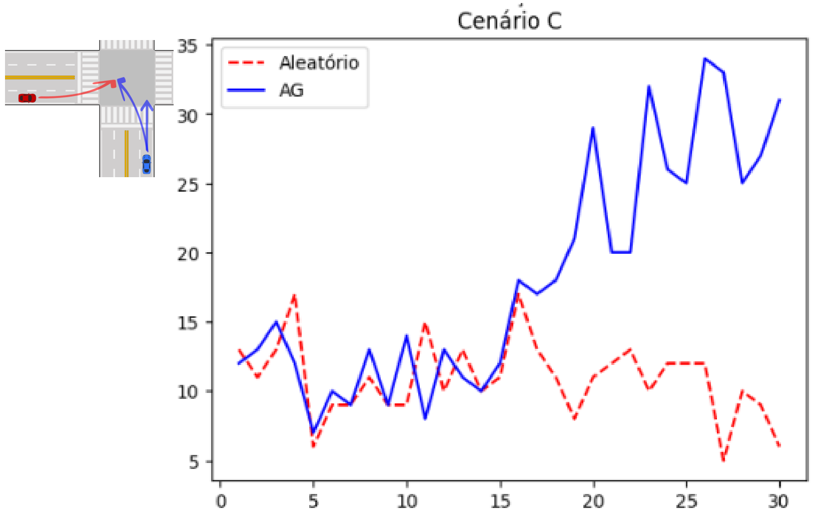
Results – Risk Level (RL) – parte (2 / 2)

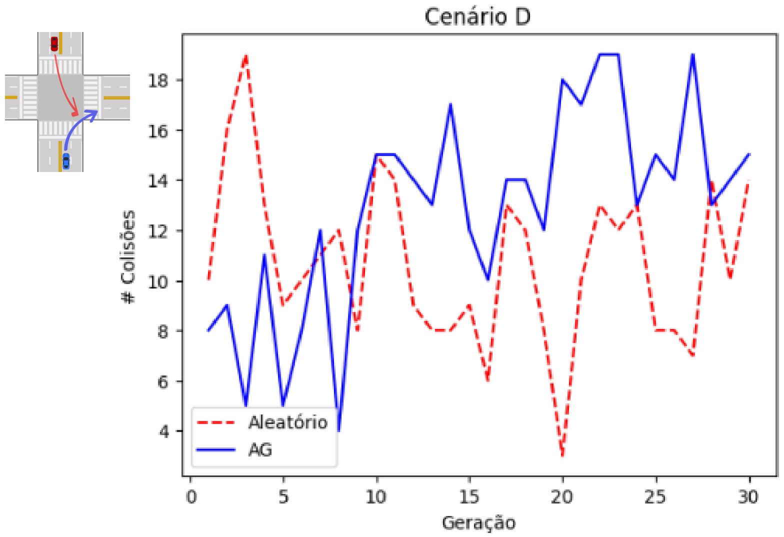
	RISK LEVEL			
SCENARIO	**GA**	**RANDOM**	**DIFFERENCE**	**GAIN (%)**
A	13,32 ± 6,68***	9,70 ± 7,69	3,62	37,30
B	7,48 ± 6,86***	6,07 ± 6,56	1,41	23,27
C	8,78 ± 6,82***	7,58 ± 6,56	1,20	15,83
D	9,84 ± 6,03***	7,53 ± 6,32	2,31	30,64
E	7,69 ± 6,71***	5,96 ± 6,18	1,74	29,15
F	10,08 ± 6,5.	9,68 ± 6,92	0,40	4,09

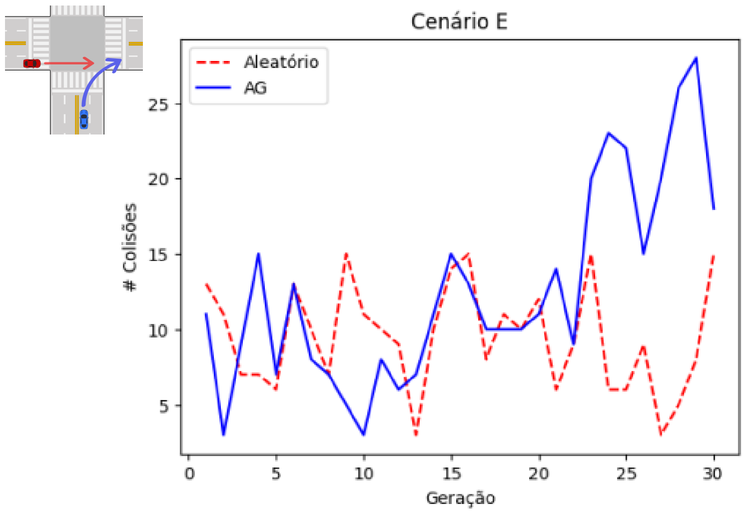
Results – Number of Collisions (NC) – parte (1 / 2)

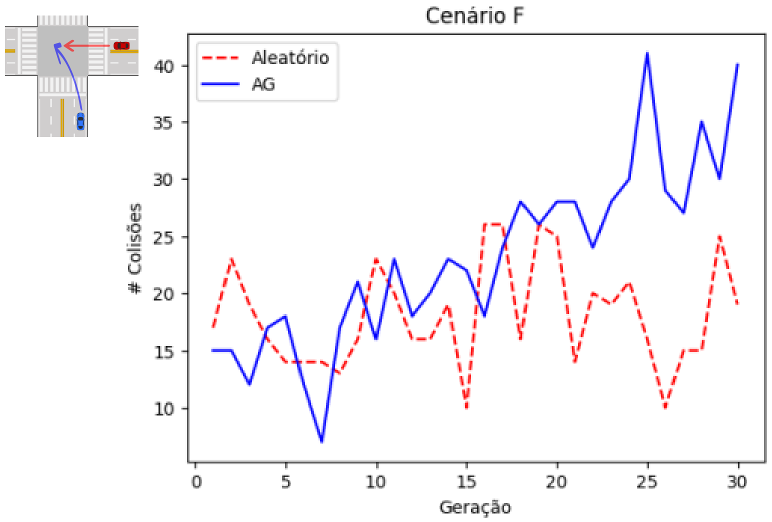








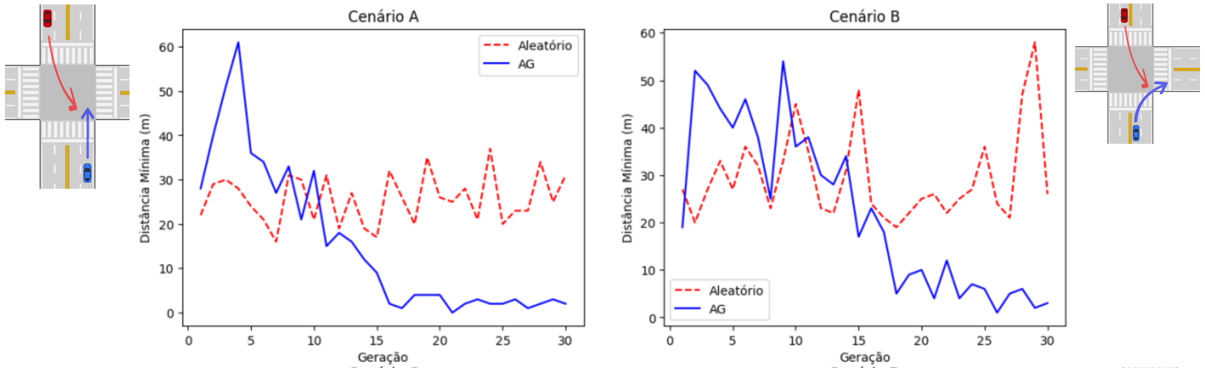


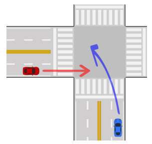


Results – Number of Collisions (NC) – parte (2 / 2)

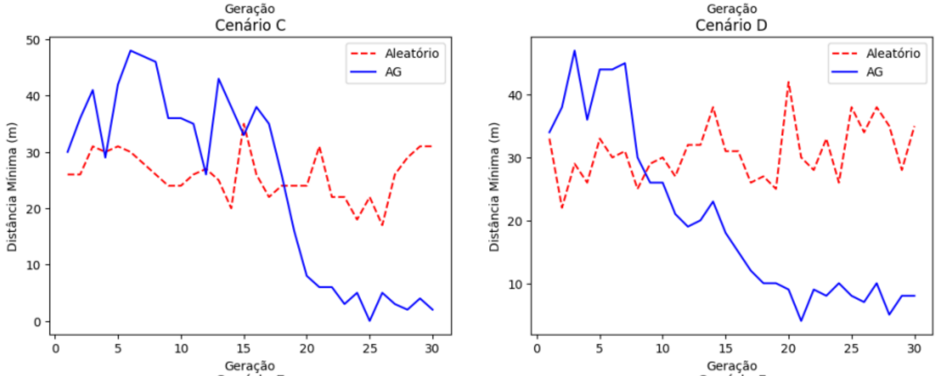
	A		B		C		D		E		F	
Summation of Generations .	RANDOM	GA	RANDOM	GA	RANDOM	GA	RANDOM	GA	RANDOM	GA	RANDOM	GA
1 - 10	223	197	97	123	107	114	123	89	100	81	169	150
11- 20	224	256	125	205	119	157	90	139	102	101	200	230
21 - 30	204	220	133	249	101	273	109	158	82	195	174	312

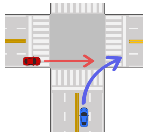
Results – Minimum Distance (MD)



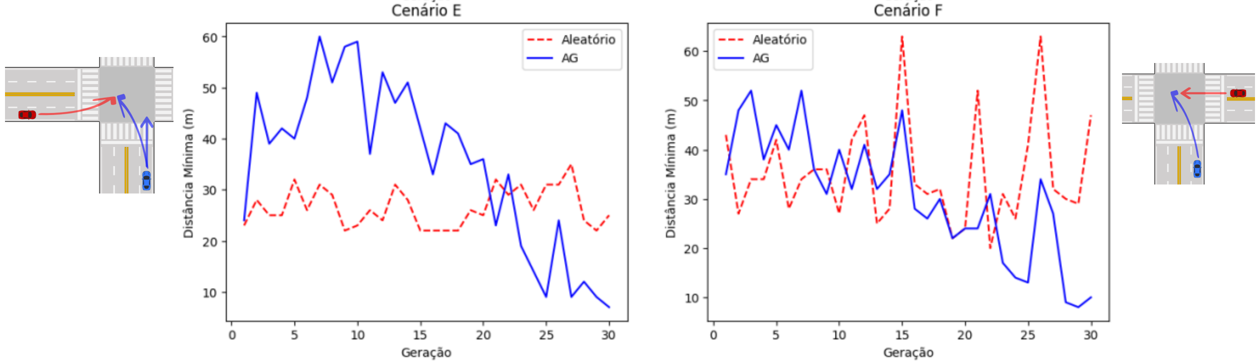


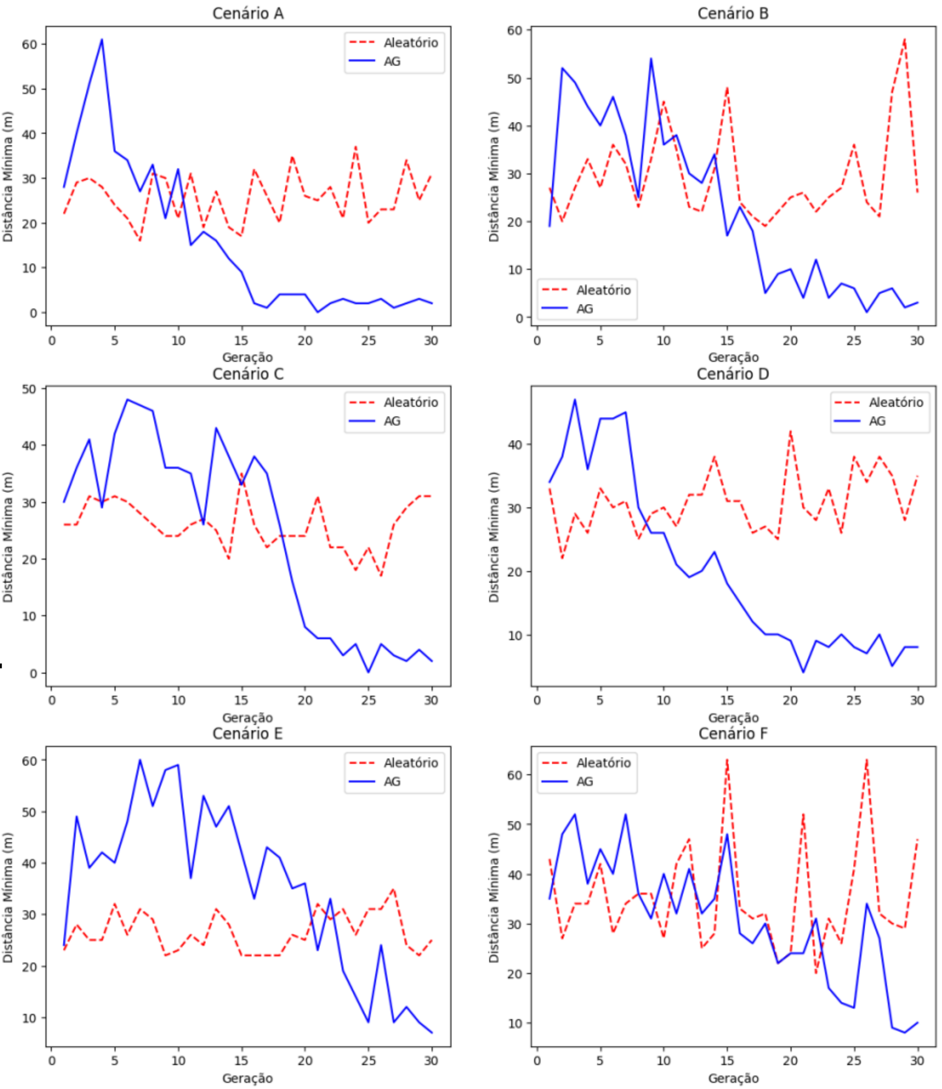
Global



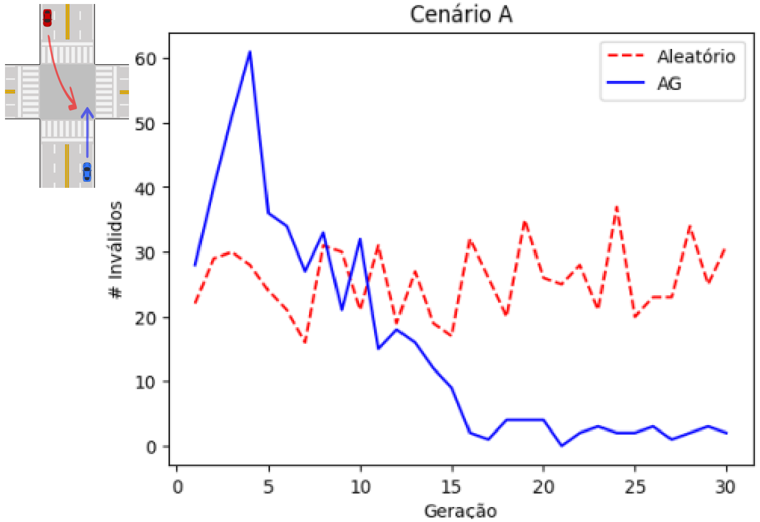


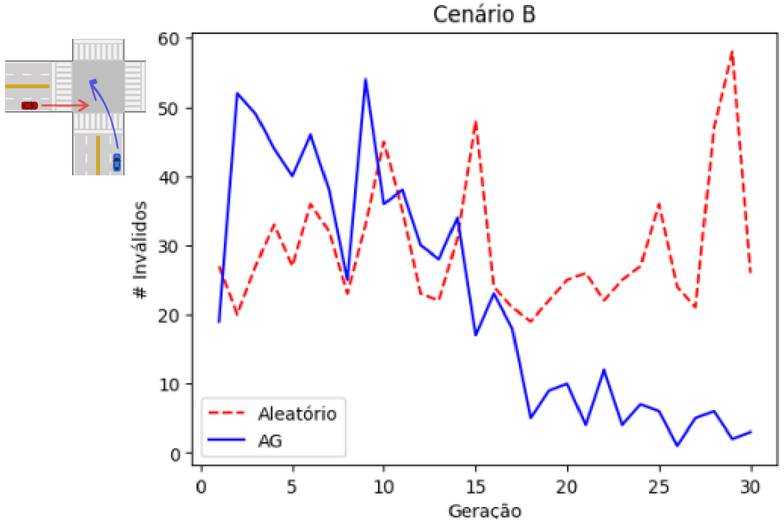
No Collision

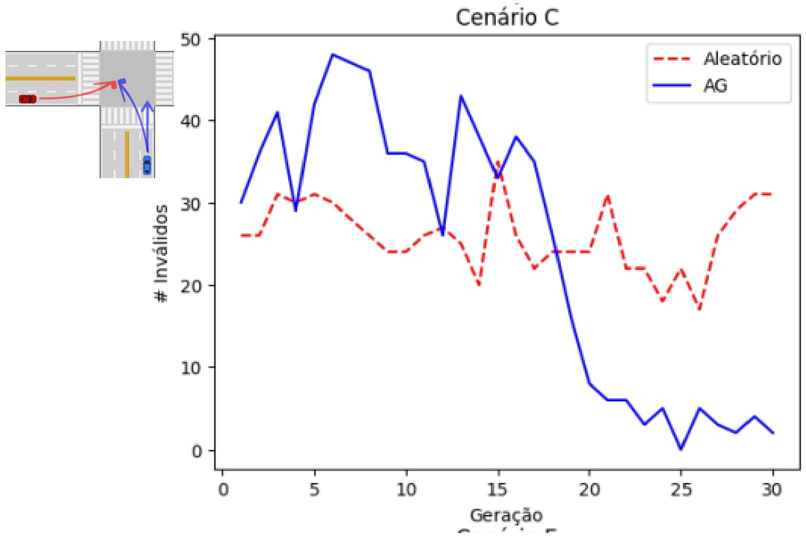


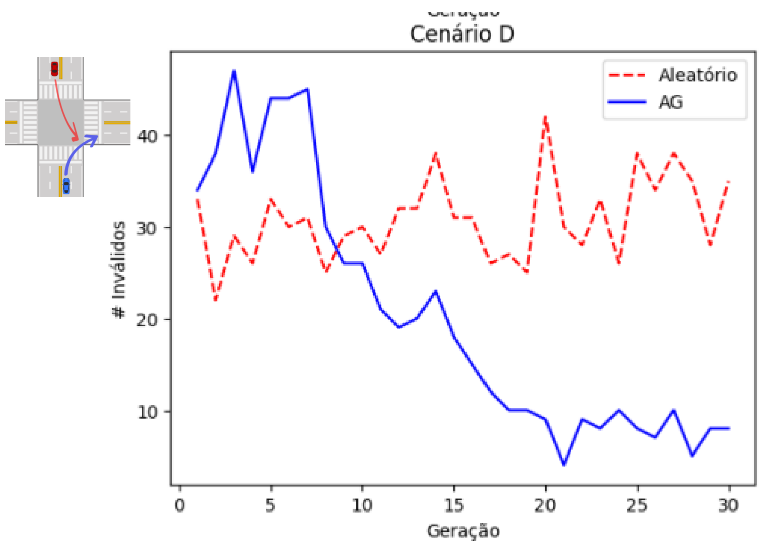


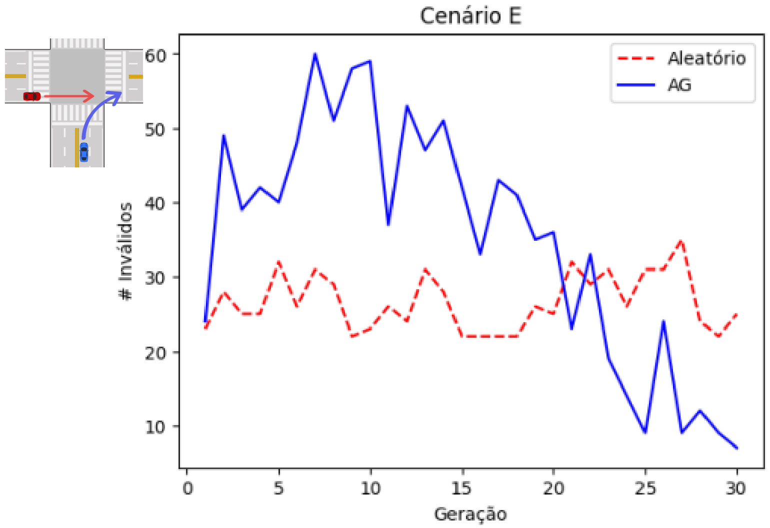
Results – Number of Invalids (NI) – parte (1 / 2)

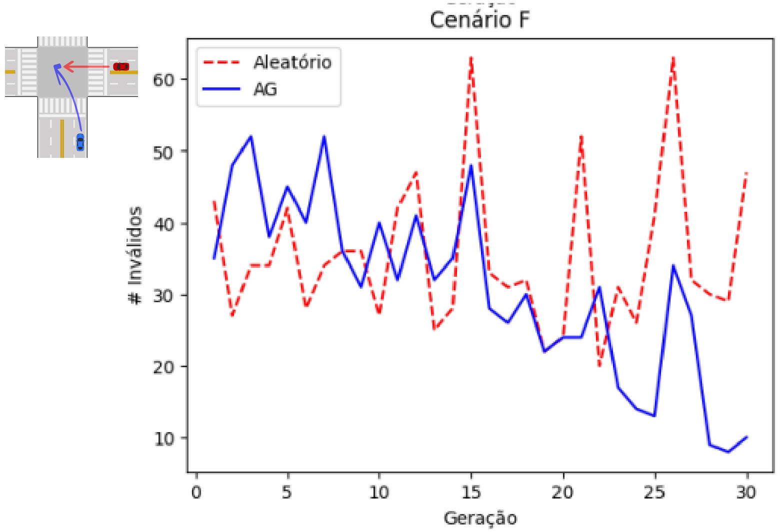












Results – Number of Invalids (NI) – parte (2 / 2)

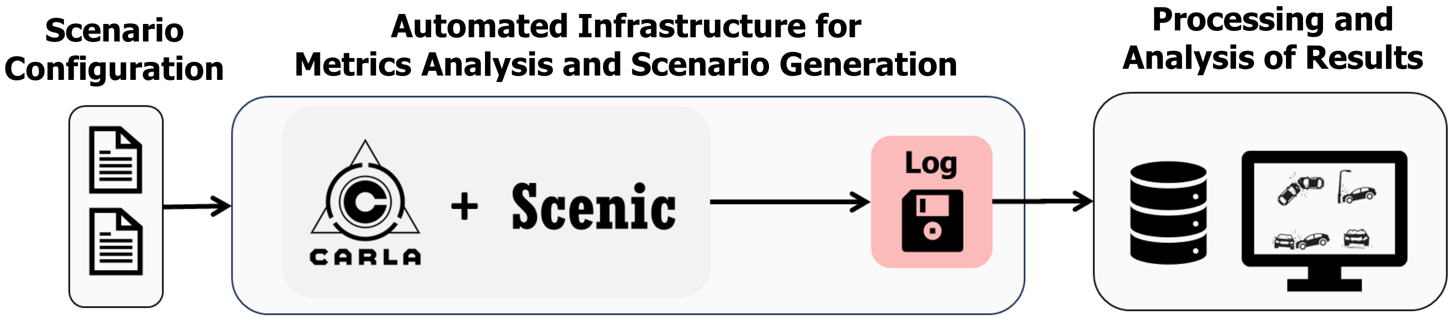
	A		B		C		D		E		F	
Summation of Generations	**RANDOM**	GA	**RANDOM**	GA	**RANDOM**	GA	**RANDOM**	GA	**RANDOM**	GA	**RANDOM**	GA
1 - 10	252	363	303	403	276	391	288	370	264	470	341	417
11- 20	252	85	270	212	253	298	311	157	248	418	347	318
21 - 30	267	20	312	50	249	36	325	77	286	159	371	187

CONCLUSIONS

Conclusions – part (1 / 3)

Developed Infrastructure

- ✓ Integration of Simulator (CARLA) and Library (Scenic) for Critical Scenario Generation.
- ✓ Architecture Based on Textual Descriptions, Enabling Vehicle Control Analysis and New Studies.

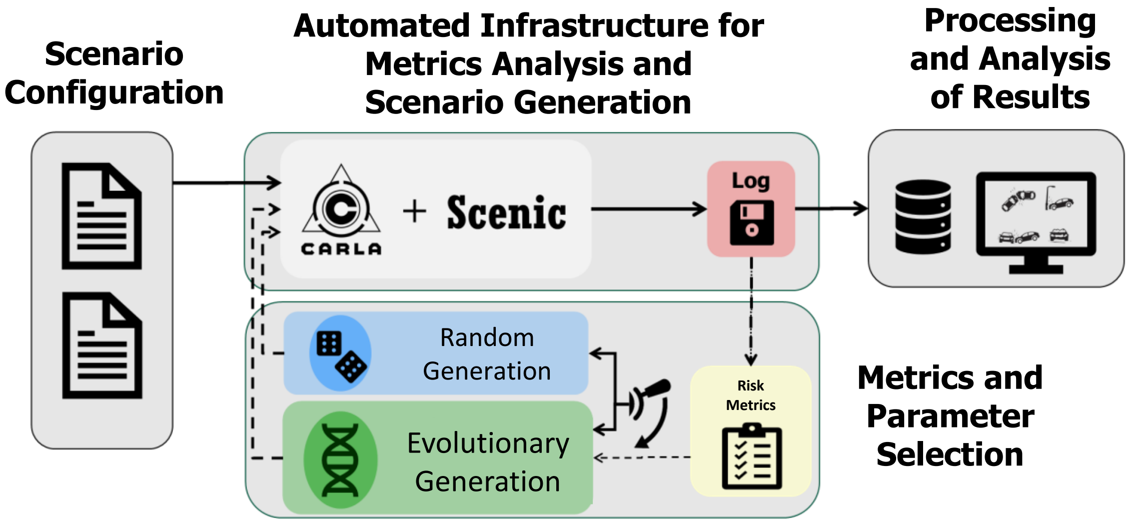


Conclusions – part (2 / 3)

Main Results

- ❑ ***Genetic Algorithm outperformed random generation in risk:***
  - ✓ Average increase of 23% in risk levels.
  - ✓ Reduction in invalid simulations (784 fewer).
  - ✓ Average minimum distance reduced from 1,806m to 1,332m.

- ❑ **Compact logs (10GB/100k simulations) enable new studies with cost savings and efficiency.**



Conclusions – part (3 / 3)

Challenges and Opportunities (Possibilities for the Master's and the Future)

- ❖ **Need for optimizations in the infrastructure for open-source contributions.**
- ❖ **Optimization of the Objective Function (meta-learning).**
- ❖ **Comparison with other search methods.**

Research Schedule

	2024												2025							
Activities	**Jan.**	**Fev.**	**Mar.**	**Apr.**	**May**	**June**	**July**	**Aug.**	**Sept.**	**Oct.**	**Nov.**	**Dec.**	**Jan.**	**Fev.**	**Mar.**	**Apr.**	**May**	**June**	**July**	**Aug.**
Refinement of the simulation infrastructure																				
Development of scenarios																				
Development of controls																				
Data collection																				
Verification and validation of results																				
Preparation of Systematic Literature Review (SLR)																				
Submission of SLR																				
Preparation of implementation article																				
Submission of implementation article																				
Writing qualification																				
Qualification exam																				
Writing defense																				
Defense presentation																				

Acknowledgments

This work was carried out with the support of Itaú Unibanco S.A., through the Itaú Scholarships Program (PBI), linked to the Data Science Center at the Polytechnic School of the University of São Paulo.

QUALIFYING EXAM

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Gabriel Kenji Godoy Shimanuki

Automatic Generation of Critical Scenarios for Evaluating Intelligent Control of Autonomous Vehicles in a Simulated Environment