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Enhancing Roundabout Efficiency Through Autonomous Vehicle Coordination

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Abstract: The paper discusses the potential for autonomous vehicles to improve traffic flow on roundabouts, suggesting that their ability to slow down strategically can enhance traffic and reduce pollution on both main and yielding roads. A traffic simulator for a roundabout was developed for a busy intersection of a new city neighborhood. We consider that some of the cars are self-driving, and they are fully aware of the traffic scenario. By optimizing their speed and timing their speed reduction, these vehicles can help maintain a balance between the number and time of crossing vehicles on both the main and yielding roads. This study evaluates the effectiveness of the intervention, demonstrating that autonomous vehicles can significantly improve roundabout efficiency, reducing congestion and pollution. The application of genetic algorithms is highlighted as an effective optimization method to find the right autonomous vehicle's timing and speed reduction ratio combination on the main road to enhance traffic efficiency.

Keywords: autonomous vehicle; traffic; genetic algorithm; traffic simulator; optimization; roundabout

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1. Introduction

Roundabouts often create bottlenecks and experience traffic congestion due to high vehicle volumes and inefficient flow management. To ensure smooth traffic and prevent congestion, the challenge lies in balancing vehicle entry and exit, particularly when yielding vehicles cause delays for those on the main road. Autonomous vehicles have the potential to optimize traffic flow by strategically slowing down to allow more vehicles to pass over the roundabout without significantly impacting traffic on the primary road. This study analyzed the traffic dynamics at a roundabout where a main traffic flow road intersected with a side traffic flow road. Vehicles on the side road were required to yield to vehicles on the main road.

Autonomous vehicles can enhance traffic flow by reducing delays, especially when their presence exceeds 45% of the traffic mix, which leads to improved efficiency in both urban and rural environments [1]. Although the primary intention of deploying autonomous vehicles is to improve traffic flow and ensure user safety, their advantages also extend to environmental sustainability. Numerous research studies have explored the potential impact of autonomous vehicles on traffic management. However, the existing literature lacks sufficient investigations addressing their strengths in mixed-traffic flow situations. As noted in previous studies [2], the impact of autonomous vehicles in mixed-traffic environments includes increased traffic capacity, improved stability, and a reduced probability of traffic breakdown, which collectively lead to a decrease in congestion waves. Previous research conducted by the authors in [3] demonstrated the implementation of an optimization framework for connected automated vehicles aimed at achieving smooth traffic flow. Through simulation validation, the study revealed a 51% reduction in travel time and a 35% reduction in fuel consumption, providing significant evidence that vehicle coordination can improve traffic movement.

The structure of this paper is as follows: Section 2 reviews related work, Section 3 explains the optimization method, the system's implementation, and simulation results, Section 4 is dedicated to discussion, and Section 5 concludes the paper.

2. Related Work

Masi presents in [4] a longitudinal route-planning method for autonomous vehicles based on coordinates provided by an HD (high-definition) map. The autonomous vehicle's localization precision enables it to create an algorithm for detecting roundabout insertion maneuvers and making optimal decisions when engaging with other road traffic participants. The proposed strategy allows an autonomous vehicle that does not have priority to enter the roundabout by performing the insertion maneuver if it does not interfere with the movement of another vehicle that has priority to pass. In [5], Wang et al. developed a control strategy based on the cooperative driving of autonomous vehicles on a roundabout to optimize the flow of vehicles and assure traffic safety, with three components:

1. Controlling traffic flow on a roundabout using nonlinear traffic optimization and state variable discretization.
2. Controlling the choice on when the autonomous vehicle should enter the roundabout by performing a probabilistic analysis of the actual vehicle flow and determining the ideal moment of insertion.
3. Vehicle platoon control using a cooperative driving strategy of the CACC (cooperative, adaptive cruise control) type, which is based on a bidirectional control architecture.

Wang et al. [6] present a grid-based image-processing system that attempts to streamline the optimal decision on how to insert autonomous vehicles on a roundabout through three stages: vehicle detection, vehicle identification and classification, and machine learning. Machine learning uses the direction and speed of movement, the permanent position, and the choice to enter the roundabout flow of vehicles as variables to estimate the ideal times and speed for an autonomous vehicle's entry to a roundabout. Banjanovic-Mehmedovic et al. [7] proposed using game theory to solve conflict scenarios between autonomous vehicles entering a roundabout. In making the insertion decision, two negotiation methods were used: noncooperative game theory, or "Nash equilibrium", based on the analysis of strategic choices concerning competitive scenarios, and cooperative game theory [8], or "Stackelberg equilibrium", based on analytical tools used to study cooperative player behavior [9]. Autonomous vehicles entering the roundabout communicate their position and angle to autonomous vehicles already on the roundabout. Circulating vehicles, which have travel priority, decide whether to slow down to enable the entering vehicle to enter the roundabout using noncooperative / cooperative theories. Cao et al. [10] investigated and highlighted the potential for autonomous vehicles to use an energy-efficient strategy when entering a roundabout by improving driving patterns or by improving driving behavior. Autonomous vehicles reduce fuel consumption for other road traffic participants on a roundabout by avoiding excessive speed drops, i.e., unnecessary stops, maintaining a steady travel speed, and adapting to the traffic flow. Boualam et al. [11] investigated the increase in road safety associated with the increased number of autonomous vehicles engaging in roundabout traffic. The scenario was investigated for increases of 0–20–40–60–80–100% in autonomous vehicles within the traffic, resulting in a reduction in the length of waiting queues as the number of autonomous vehicles increased, in addition to an implied gain in road traffic safety. Farkas et al. [12] presented the application of model predictive control (MPC) on autonomous vehicles when entering a roundabout to manage the travel speed of each autonomous vehicle, to achieve the optimal operational efficiency and safety. Thus, the predictive controller of each autonomous vehicle will calculate the speed variation at each point in time of movement based on data about the other vehicles' situations, which are provided by a centralized controller. Autonomous vehicles in the vicinity communicate with the centralized controller using V2X (Vehicle-to-Everything) technology. Martin-Gasulla et al. [13] developed a single-lane roundabout traffic management system to control the flow of autonomous vehicles over a roundabout. The management system prioritizes vehicles entering using a technique based on the shortest time of insertion, SRTF (Shortest Remaining Time First), thereby resolving any conflicts with autonomous vehicles on the circular route. In [14], García Cuenca et al. developed a machine learning model to predict the autonomous vehicle speed and steering angle based on traffic data and roundabout design. The predictive model was developed using the following machine learning techniques:

1. SVM (Support Vector Machine) is a regression method that maintains all of the algorithm's primary properties.
2. Linear regression predicts the speed and steering angle when entering a roundabout.
3. Multilayer, deep neural networks incorporate feed-forward and adaptive learning functions to prevent delayed convergence.

Severino et al. [15] used computer simulation to evaluate the performance and safety of a roundabout with a heterogeneous road traffic composition of 75% conventional vehicles (CVs) and 25% connected autonomous vehicles (CAVs). The findings of the analyses conducted after computer simulations revealed that the presence of CAVs in roundabout traffic increased the dynamic performance of all vehicles in the traffic and reduced conflicts when changing the flow of vehicles. Machine learning models offer realistic solutions that improve energy efficiency and reduce emissions in self-driving roundabouts. These models are trained by simulating various scenarios, such as rerouting vehicles, altering traffic lights, and limiting some types of vehicles in high-pollution zones. Air pollution levels can be accurately predicted by using data on vehicle types, traffic patterns, meteorological conditions, and air quality measurements, as well as algorithms such as Gaussian Naive Bayes, Support Vector Machine, and XGBoost [16].

Subramaniam et al. [17] presented an overview of artificial intelligence models and machine learning algorithms utilized in environmental pollution forecasting and warning systems. Traditional statistical methods for air pollution forecasting include ARIMA (Autoregressive Integrated Moving Average) and the gray model (GM). The following neural network models have been used for air pollution prediction: BPNN (Back Propagation Neural Network), ELM (Extreme Learning Machine), LSTM (Long Short-Term Memory), GRNN (Generalized Regression Neural Network), GRU (Gated Recurrent Unit), WNN (Wavelet Neural Network), fuzzy logic model, and SVM.

3. Optimization of the Roundabout Traffic Through Autonomous Vehicle Coordination

Gkyrtis et al. [18] classify roundabouts into three groups based on their size and number of lanes: mini-roundabouts (designed for urban areas with low traffic), single-lane roundabouts (which feature one traffic lane), and multi-lane roundabouts (which have two or more traffic lanes). Although the maximum recommended entry speeds are 25 km/h for mini-roundabouts and 35 km/h for single-lane roundabouts, traffic monitoring has recorded slightly higher speeds in practice. Typical speed profiles for vehicles approaching a roundabout are presented in [19], adapted in [18].

Understanding the complex connections between traffic laws, road design elements, and the maneuvers applied by different road users is necessary for autonomous driving at roundabouts. Roundabouts can be safer than traffic-signalized intersections for autonomous vehicles, as advancements in sensors allow these vehicles to navigate merges across different traffic lanes more effectively [20].

According to Mandavilli et al. in [21], actual roundabouts are among the safest and most efficient methods for managing intersections and improving traffic flow. They also have the added advantage of reducing fuel consumption and vehicle emissions by minimizing the time vehicles spend idling at intersections, which is beneficial for the environment.

3.1. The Analyzed Roundabout and the Traffic Simulator

This study investigates an important roundabout located at the edge of a new residential neighborhood in the city of Brașov. This neighborhood, home to approximately 20,000 residents, has several connections with the city center and industrial areas, but the primary access is the shortest one via Lacurilor Street and Poienelor Street. Here, the Decathlon roundabout represents the connection point between this new neighborhood and the main access streets to the city center and the neighboring villages.

During the morning hours, a significant number of vehicles, estimated at around 6000–7000, exit the neighborhood. Of these, approximately 2000 to 3000 vehicles pass over the Decathlon roundabout. This roundabout intersection connects four two-lane streets and has a diameter of 22 m. The peak traffic period at the roundabout occurs between 7:30 AM and 8:30 AM, a time when the volume of traffic is significantly elevated. During this hour, around 1000 vehicles navigate the roundabout. Outside of this morning rush hour, traffic flow generally decreases, with volumes typically ranging from 300 to 600 vehicles per hour. This variation in traffic patterns suggests that the roundabout experiences a substantial spike in activity during the early morning due to commuters heading to work or taking children to school.

A comprehensive analysis of the roundabout's entrances reveals a distinct preference for the street at the bottom of Figure 1. This street links the residential district to the city and is where the heaviest traffic takes place. According to Romanian traffic rules, vehicles approaching the roundabout from the right have the right of way. This means that drivers must yield to any vehicles already circulating within the roundabout before entering. This prioritization promotes efficient traffic flow while minimizing the risk of accidents. To enhance clarity, all four streets that lead into the roundabout are clearly marked with "give way" traffic signs.

The observed traffic pattern suggests that priority is established for vehicles entering from the right lane, the street on the right side, as illustrated in Figure 1. This street connects some shopping areas and is of secondary importance. On this road, there is normal traffic on most days, around 400 vehicles/hour, meaning that the distance between two consecutive vehicles (Figure 2) is rather large most of the time. Thus, vehicles from the busy street can easily cross the intersection during off-peak hours, and the traffic is light. This is not the case in peak hours (Figure 2), and long queues form most of the time. In this study, we will refer to the road with low traffic as the main road, while the one leading to the residential area will be the yielding road (Figure 1).

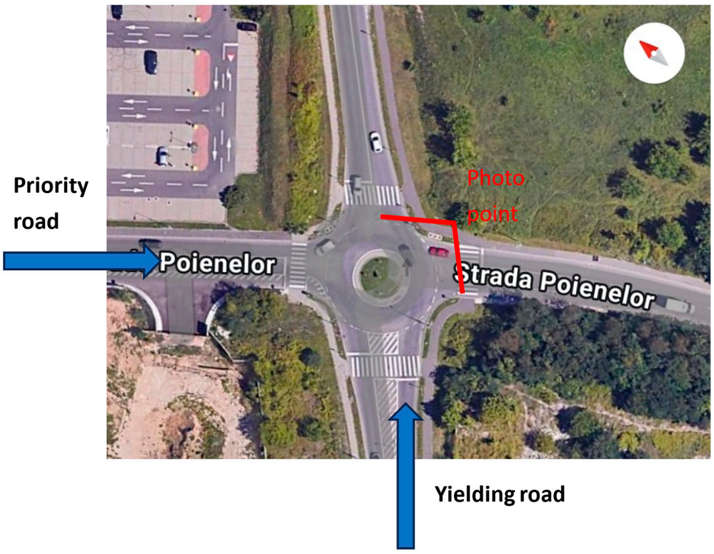


Figure 1. The analyzed roundabout connects a new neighborhood with the city center.

Figure 2. Snapshot of the traffic on the considered roundabout with heavy traffic in one direction (left) and light traffic in the other.

To study the impact of autonomous vehicle cooperation on the traffic at this intersection, we will assume that autonomous vehicles make up 10% of the traffic on the main road. This figure represents an optimistic future scenario and can be achieved in the next 10 years [22]. Even if the overall number of vehicles does not increase as anticipated, the results will remain relevant. If the proportion of autonomous vehicles were to rise, it is likely that they would collaborate differently and share information, resulting in improved traffic flow in all directions.

3.1.1. The Traffic Simulation Program

The roundabout traffic simulation program was developed in the MATLAB programming language using object-oriented principles. The program's design is based on the understanding and consideration of traffic rules, traffic patterns, drivers' behavior, and initial conditions, ensuring an accurate simulation of real-world traffic conditions. The program is based on the observation that the yielding roads experience a higher volume of vehicles, which results in a shorter distance between consecutive vehicles than on the priority road.

The initial data of the simulated scenario and the behavior of the vehicles are outlined below, based on [23,24]:

- The number of vehicles on the priority road is 55.
- The number of vehicles on the yielding road is 60.
- The roundabout radius is 11 m.

- Initial speed of all vehicles is 48 ± 3 km/h, uniformly distributed.
- Safe acceleration is 2.3 ± 0.4 m/s^2, uniformly distributed.
- Safe deceleration is 2.1 ± 0.4 m/s^2, uniformly distributed.
- Initial distance on the priority road is 35 ± 4 m, uniformly distributed.
- Initial distance on the yielding road is 18 ± 4 m, uniformly distributed.
- Imposed speed in the 30 zone is 29 ± 3 km/h, uniformly distributed.
- Imposed speed in the 50 zone is 48 ± 3 km/h, uniformly distributed.
- Initial distance from the roundabout in both directions is 70 m.

A snapshot of the simulation program is shown in Figure 3. Rectangles represent the vehicles of the simulation, green for the ones on the priority road and red for the ones on the yielding road.

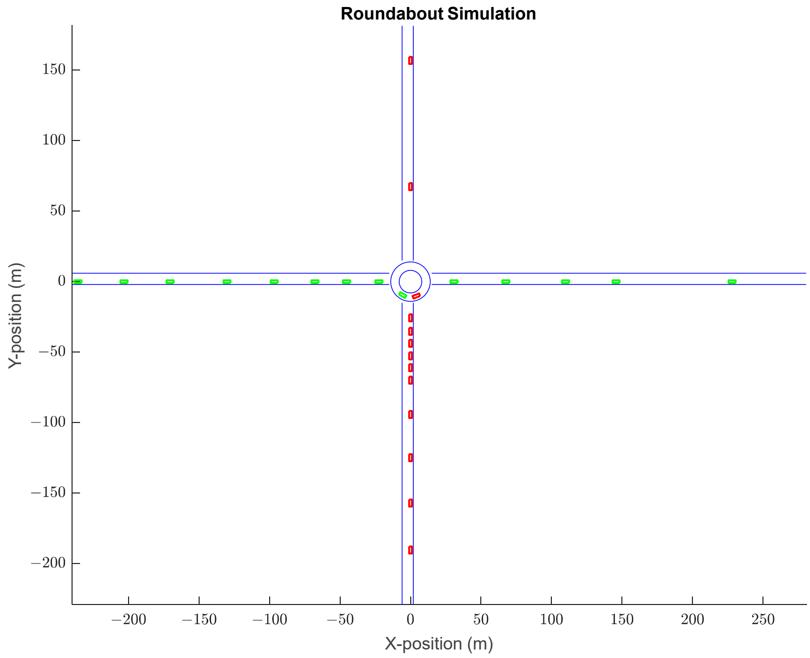


Figure 3. Snapshot of the simulation program with green-colored vehicles on the priority road and red-colored vehicles on the yielding road.

3.1.2. The Autonomous and the Manual-Driven Vehicle Models

The simulation program architecture is organized hierarchically across three levels, inspired by the behavioral patterns of human drivers, and incorporates advanced technologies for effective control and navigation. A behavior is defined as a series of actions that address a driving situation. The three levels of the control program are strategic, tactical, and control. The strategic level outlines the overall task the vehicle must accomplish, such as reaching its destination. The tactical level manages these tasks using rule-based or knowledge-based behaviors, while the control level is responsible for executing them.

The program manager from the tactical level is tasked with proposing appropriate behaviors. It does so using a database of facts, a knowledge base of rules, and an inference engine. This system also has the ability to maintain, modify, or abandon the current behavior or task. A rule-based expert system is responsible for selecting the appropriate behavior [25–27]. This vehicle model is used for both manual and autonomous vehicles in the simulation program. In [28], Liang et al. demonstrated that a multi-agent system-based distributed control architecture, together with a hierarchical controller, can effectively handle the cooperation control of autonomous vehicles in typical traffic scenarios.

We used official traffic regulations to define access areas, speed limits, and priority rules in order to model car traffic in the roundabout area accurately. As a result, we identified four distinct areas where specific rules define behaviors. The rules prioritize road safety to avoid collisions with other participants and to obey official regulations [29]. These rules encompass adjusting speed to adhere to the legal limits in different zones, maintaining a safe following distance relative to the speed of the vehicle ahead, and yielding to vehicles on priority roads. Vehicles on the yielding road will either slow down or come to a complete stop if a vehicle is on the main road within a distance of 11 ± 3 m. This distance is shorter if the vehicles are approaching at low speeds and longer if they are approaching at higher speeds.

- Deceleration Area: This segment is where traffic slows from 50 km/h (the speed limit in urban areas) to 30 km/h (the speed limit before and on the roundabout). This area is located 25 to 50 m from the roundabout.
- Roundabout Area: In this zone, drivers need to pay close attention, and the speed limit is set at 30 km/h. This area extends up to 25 m from the roundabout, where vehicles from the yielding road must slow down or even stop to allow vehicles on the priority road to pass.
- Conflict Zone: This zone is located on the roundabout, where vehicles interact with those entering from other entrances.
- Acceleration Zone: This area is designated for vehicles exiting the roundabout.

In the scenario shown in Figure 3, the red cars approaching from the bottom must give way to the green vehicles that are approaching or are already in the conflict zone, entering from the left.

In the simulated scenarios, we considered that vehicles enter the roundabout and proceed straight from the two roads, priority and yielding. While this scenario may not reflect real-world conditions, it represents the most plausible situation during peak traffic periods. Both roads are one-lane roads positioned at 90-degree angles to each other, without the possibility of overtaking.

3.2. The Baseline Roundabout Traffic Model

To evaluate the effectiveness of autonomous vehicle interventions with traffic flow, baseline models were developed. These simulations focused on roundabout traffic, considering the passage of 55 vehicles over an extended period. During this time, we measured the duration required for these vehicles to pass and recorded the number of vehicles exiting the roundabout from the yielding road. In scenarios without autonomous vehicles on the main road, the vehicles maintained relatively large and approximately equal distances from one another, while those on the secondary road faced reduced opportunities to enter the roundabout. This will lead to a slowdown, with vehicles stopping and forming a queue on the yielding road (Figure 3). Given that vehicles vary in speed and drivers accelerate differently, we created 10 initial scenarios that account for these variations in initial position, distances, speeds, and accelerations.

In Figure 4, the blue line represents the evaluations of the ten basic scenarios, revealing that fifty-five vehicles on the main road take 171 to 172.5 s to pass the intersection, while the red dotted line shows that six to eleven vehicles on the secondary road pass during that time. This illustrates a significant challenge in managing the traffic flow and emphasizes the need for careful consideration in traffic management strategies.

Figure 5 illustrates the speed profile in one of the scenarios (nr. 1). It shows how vehicles accelerate and decelerate to keep pace with the vehicle ahead, how they maintain their speed to follow the preceding vehicle, and how they come to a stop on the yielding road. In Figure 5a, vehicles on the priority road are required to stop, but they only slow down to adjust for their cornering speed before accelerating upon exiting the roundabout. In Figure 5b, on the yielding road, the first vehicle passes over without stopping, the second vehicle has to stop for about 3 s, and all subsequent vehicles must wait for over 10 s. During the simulated 100 s, only seven vehicles are able to pass over the roundabout, resulting in a queue where the remaining vehicles experience stop-and-go behavior.

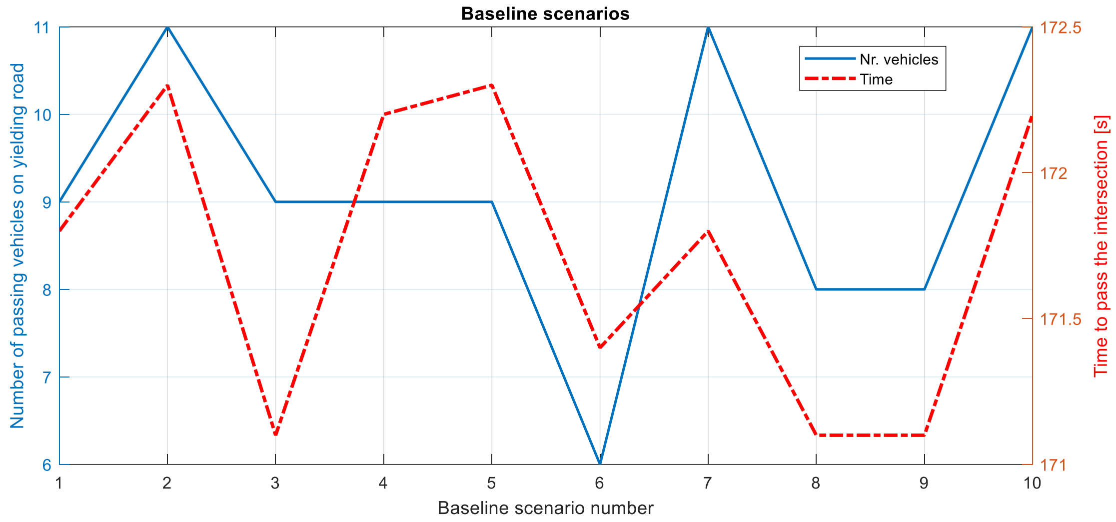
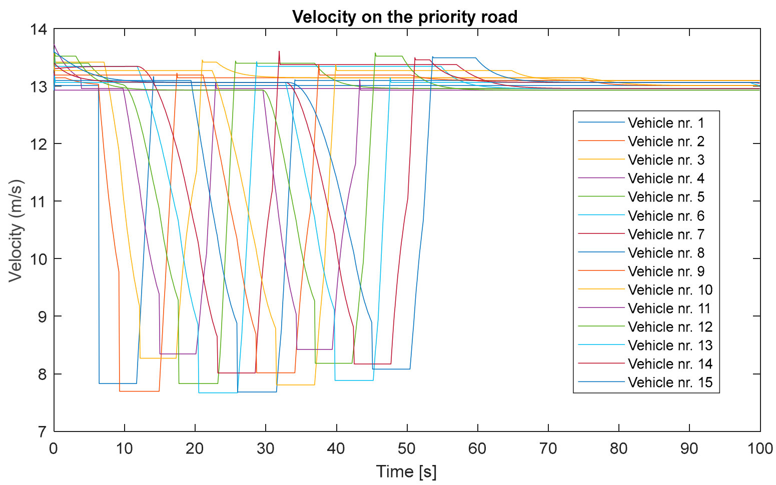
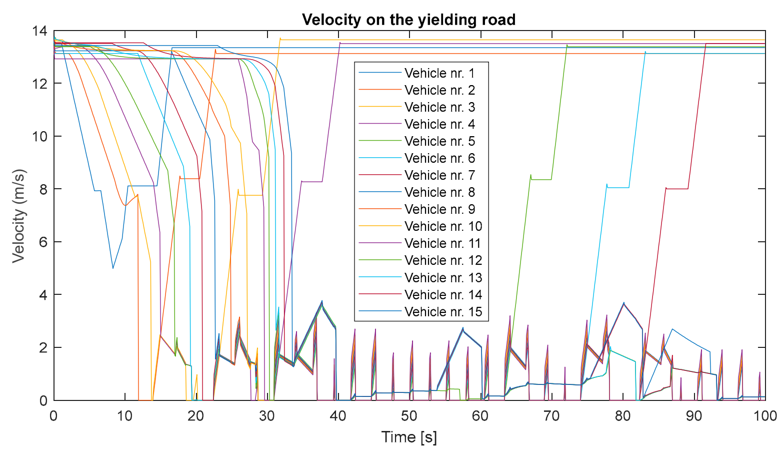


Figure 4. Performance metrics at the 10 baseline scenarios.



(**a**)



(**b**)

Figure 5. The velocities in one of the baseline scenarios for the first 15 vehicles: (**a**) priority road; (**b**) yielding road.

3.3. The Effect on the Roundabout Traffic of the Autonomous Vehicle Slowdown

The introduction of autonomous vehicles into urban traffic worldwide is currently limited, but significant growth is expected in the near future. There is a strong emphasis on enhancing traffic efficiency using the existing infrastructure [30]. Projections suggest that sales of autonomous vehicles will begin to rise in 2025, with an estimated 1.3 million units sold over the subsequent five years. Furthermore, their usage may reach 36 million vehicles within the next decade [31]. By 2050, it is anticipated that 80–100% of all cars sold will be autonomous [32]. According to Lu et al., even a penetration rate of just 10% for autonomous vehicles is expected to provide significant benefits for future traffic management, as well as reductions in emissions and fuel consumption.

To evaluate autonomous vehicle control over traffic, we considered that 10% of the vehicles in the simulated scenario are autonomous, meaning every 10th vehicle—specifically, 5 out of the 55 vehicles. These autonomous vehicles are aware of the environment and traffic conditions and decide to reduce their speed at a certain distance from the center of the roundabout. This decision results in variable spacing between vehicles on the main road, allowing a greater number of vehicles from the yielding road to pass through the intersection. However, it is crucial that this decision to decelerate is not made from too great a distance. If it is, the traffic on the main road could be severely disrupted, potentially resulting in a jam that blocks the access for vehicles on the yielding road. This highlights the importance of timely and contextual decision-making by autonomous vehicles to enhance overall traffic efficiency. A snapshot of the simulation program is presented in Figure 6. Here, the gap among the vehicles on the priority road allows five vehicles to pass on the yielding road.

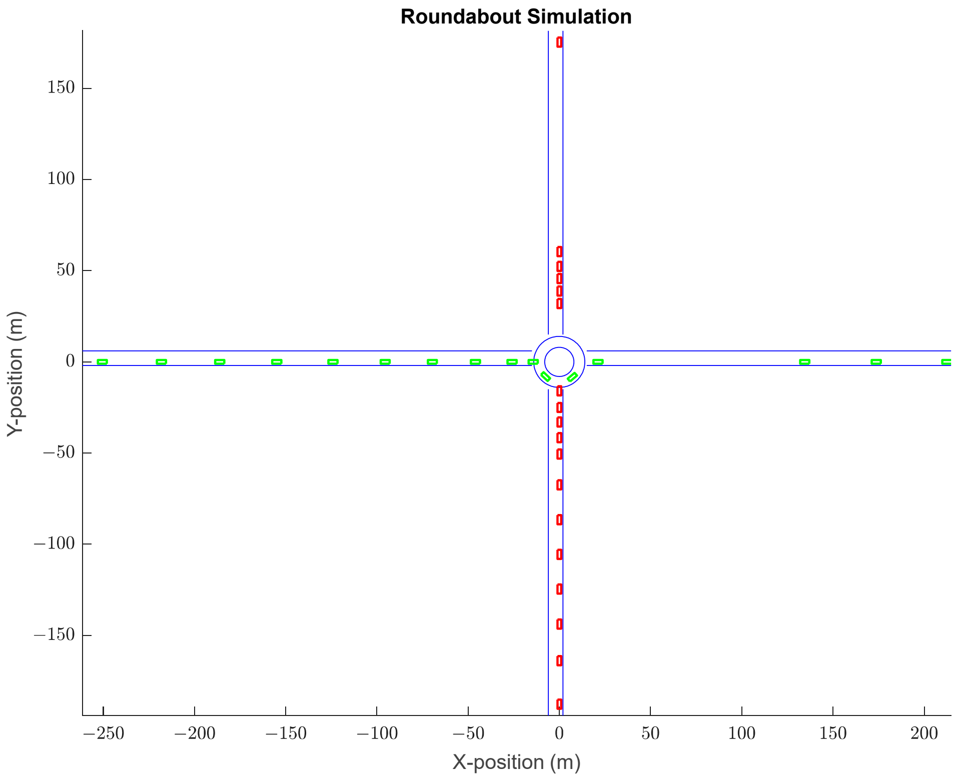
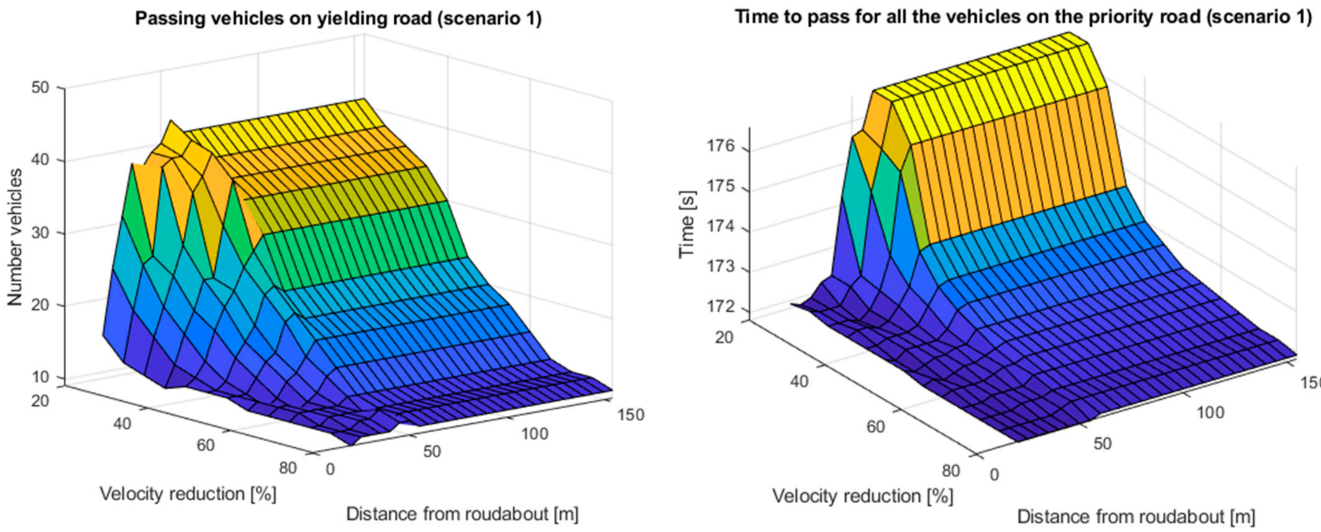


Figure 6. A snapshot of the simulation program where green-colored vehicles purposely decelerate and form a significant gap.

An evaluation of the deceleration effect was conducted by measuring the number of vehicles on the secondary road that passed over (Figure 7a) and the total duration of the simulation, ensuring all 55 vehicles passed over the intersection (Figure 7b). The assessment was conducted using various combinations of percentages of maximum imposed speed in relation to the permitted speed for each road section. It analyzed the effect of speed reduction by 20% to 80% in increments of 5%. Additionally, the distance at which deceleration began to reach the target speed ranged from 20 to 160 m, with intervals of 5 m (Figure 7).



(a) (b)

Figure 7. Evaluation of the effect of autonomous vehicle slowdown on the traffic on the roundabout with different percentages of velocity reduction and at different distances from the roundabout: (**a**) the number of vehicles that can pass from the yielding road; (**b**) the time for all vehicles to cross the roundabout on the priority road.

The evaluation revealed that the two objectives are contradictory. If we aim to increase the number of vehicles passing over the roundabout on the secondary (yielding) road, the time taken for vehicles on the main (priority) road to pass will inevitably increase. Additionally, it is observed that beyond a certain limit (approximately 60 m in the case of Scenario 1), further distance does not affect the outcome; instead, only the percentage of speed reduction matters.

Since this study was conducted using five percent increments and distances of 5 m, not all combinations were analyzed. We can assume that there is a combination of percentage and distance that can simultaneously achieve both objectives: a high number of vehicles and a low travel time. This can only be accomplished through a mathematical optimization method.

3.4. The Optimal Decision of the Autonomous Vehicles for Traffic Optimization

When seeking to optimize traffic flow at a selected roundabout using autonomous vehicle cooperation, we face conflicting objectives. On the one hand, we aim to increase the number of vehicles passing over the intersection from the yielding road. On the other hand, we want to minimize disruption to the traffic on the priority road. A suitable approach to address this dilemma is to employ a multi-objective optimization algorithm.

One such algorithm designed for this type of problem is the evolutionary algorithm, particularly the multi-objective genetic algorithm [33]. This algorithm is inspired by the process of biological evolution and utilizes principles of natural selection and genetics. Initially, a population of potential solutions is generated, which then evolves through a process similar to Darwinian selection. Variations within the population are introduced using genetic operators such as crossover and mutation. Over several generations, this process helps to refine and improve the solutions.

In their published papers, researchers such as Reda et al. [34], Choi et al. [35], and Gallelli et al. [36] have focused on genetic algorithms, which they regard as some of the strongest evolutionary algorithms due to their replication of the principle of survival-of-the-fittest solutions. These researchers utilized evolutionary algorithms to estimate and optimize various parameters, calibrate datasets, and plan traffic routes.

Genetic algorithms are effective in solving complex optimization problems across various aspects of autonomous vehicle systems, thereby enhancing performance in navigation, control, and path planning. They are used to optimize control parameters in systems like cruise control and maneuvering, which can lead to better driving accuracy and comfort [37]. Additionally, these algorithms are employed for path planning, integrating multiple tasks such as path estimation and collision avoidance, ultimately improving safety outcomes [38]. By combining model predictive control with genetic algorithms, we can effectively tackle nonlinear path-tracking challenges in autonomous vehicles. This integrated approach facilitates flexible optimization of the vehicle's trajectory and has shown superior performance in both simulations and real-world tests [39].

The strength of metaheuristic algorithms lies in their independence from specific problems, enabling them to find optimal solutions in challenging search spaces. Additionally, these algorithms are less prone to becoming trapped in local minima compared to gradient-based approaches. Our goal function is multimodal, discontinuous, and non-differentiable, and the evolutionary algorithm is particularly well-suited to addressing these complexities. It can effectively locate optimal solutions within intricate search areas.

The multi-objective genetic algorithm optimizes multiple conflicting objectives simultaneously. In this case, the goals are to maximize the number of vehicles while minimizing total delay. To balance these conflicting objectives, we used a weighted sum approach, defining the fitness function as follows:

$$\text{Fitness} = w_{veh} \times N + w_{time} \times T, \tag{1}$$

where N represents the number of vehicles, T is the total simulation time (with all 55 vehicles on the priority road leaving the roundabout), and w_{veh} and w_{time} are the weights assigned to these two variables. A weight of -2 was assigned to the number of vehicles (to prioritize its maximization), while a weight of 1 was assigned to the total delay, indicating a slightly lower priority. The final outcome is a set of Pareto-optimal solutions that represent the optimal trade-off between the number of vehicles and the total simulation time.

After optimizing the 10 randomly generated models (the baseline models), the results shown in Table 1 were obtained. The findings indicate that the most effective decision under the given conditions is to reduce speed by 30 to 40%, with deceleration occurring at distances between 50 and 100 m. In all 10 scenarios, traffic conditions improved significantly, allowing a considerable number of vehicles to pass through the intersection. There was a remarkable increase in the number of vehicles on the yielding road, ranging from 245% to 583%. Importantly, these changes did not have a significant impact on the movement of vehicles on the priority road; their passage through the roundabout experienced only a slight increase in travel time, ranging from 0.41% to 1.39% (approximately 0.7 to 2.4 s).

Table 1. Genetic algorithm optimization for all ten models.

Baseline Model	Velocity Reduction	Distance from Round-about	Nr. Crossing Vehicles	Crossing Time	Time Increase	Vehicle Number Increase	Vehicle Number Increase	Crossing Time Increase
Nr.	**%**	**[m]**	**Nr.**	**[s]**	**[s]**	**Nr.**	**%**	**%**
1	**40**	**92.32**	40	173.6	1.8	31	344.44	1.05
2	**39**	**152.11**	44	174	1.7	33	300.00	0.99
3	**42**	**118.70**	36	172.4	1.3	27	300.00	0.76
4	**36**	**104.41**	41	174.6	2.4	32	355.56	1.39
5	**39**	**137.13**	38	173.7	1.4	29	322.22	0.81
6	**33**	**50.84**	41	172.2	0.8	35	583.33	0.47
7	**30**	**45.86**	44	172	0.2	33	300.00	0.12
8	**36**	**54.93**	41	172.1	1	33	412.50	0.58
9	**33**	**52.07**	41	171.8	0.7	33	412.50	0.41
10	**38**	**85.57**	38	173.7	1.5	27	245.45	0.87
Mean	37	89.39	40.4	173.01	1.28	31.3	357.60	0.74

3.5. The Roundabout Traffic Optimization

The genetic algorithm used in the optimization process returns the optimal distance and velocity combination for the vehicle number increase on the yielding road and crossing time decreases on the main road. This optimization process cannot be applied universally due to its high calculation time, and it requires immediate action when specific traffic conditions are met—specifically, a distance of about 35 m between vehicles on the main road and heavy traffic on the secondary road. Therefore, average values for the percentage reduction in speed and for the distance were calculated for the ten optimized models (Table 1). As shown in Figure 7a, distance is not a significant factor, and the chosen percentage enables a substantial number of vehicles on the yielding road to pass successfully.

The ten baseline models were simulated utilizing the average values from the optimization process. Table 2 presents the number of vehicles that successfully crossed and the time for the vehicles on the priority road, along with a comparison of these results with those obtained through genetic optimization for each model. It is evident that some models, when using these average values, performed similarly to the optimized ones; however, in certain cases, the number of vehicles decreased by as much as eight. In the case of the baseline model 3 (Table 2), an increase in the number of vehicles was observed; this improvement was achieved only by extending the time for the vehicles on the priority road.

Table 2. The performances of the 10 models using the mean optimization values for the distance and velocity reduction ratio from Table 1 and the comparison with the optimal results obtained with genetic optimization.

Baseline Model	Nr. Passing Vehicles on the Yielding Road	Time for Crossing on the Priority Road [s]	Vehicle Nr. Decrease on the Yielding Road	Time Increases on the Priority Road [s]
1	37	174.6	3	1
2	40	174.7	4	0.7
3	37	173.5	−1	2.4
4	33	174.3	8	−0.3
5	38	174.2	0	0.5
6	41	173.7	0	1.5
7	39	174.9	5	2.9
8	33	173.6	8	1.5
9	33	173.6	8	1.8
10	35	173.9	3	0.2
Mean	36.6	174.1	3.8	1.09

When comparing the performance of the ten baseline models using the average values obtained from the optimization process (as shown in Table 2), along with the performance metrics of the baseline models (illustrated in Figure 4, with a mean time of 171.7 s and an average of 9.1 vehicles), we can observe a significant increase in the number of vehicles able to pass through the yielding road (see Figure 8). Among the ten baseline scenarios, 80% demonstrated an increase in traffic volume ranging from 260% to 310%. The best-performing scenario, scenario number 6, achieved a remarkable 570% increase in traffic volume, while the worst result came from scenario number 10, which saw an increase of 220%. In contrast, the traffic on the main road experienced only a slight delay as all 55 vehicles passed through the intersection, with an average increase of approximately 2.4 s. Seven scenarios recorded delays between 2.3 and 2.8 s; only two scenarios (5 and 10) had delays below 2 seconds, while one scenario (7) exceeded 3 seconds. These results indicate that the precomputed average values obtained from the optimization process have a significant impact on traffic optimization.

Figure 8. The optimized traffic for the 10 models compared with the baseline simulations.

4. Discussion

This study began with ten scenarios involving autonomous vehicles and manually driven vehicles. The ten models were simulated with variations in parameters such as acceleration, speed, and the initial positions of the vehicles. It was assumed that, on the priority road, there are also autonomous vehicles that could help improve traffic flow. The initial hypothesis stated that the roundabout under examination is located at the intersection of two roads—one with heavy traffic and the other with lighter traffic. This hypothesis is relevant to many intersections, especially during peak hours when there is a tendency for vehicles to move from residential areas to the city center.

The simulation of ten models revealed that on the heavily trafficked yielding road, only a few vehicles are able to pass through the roundabout. To address this, the intervention of autonomous vehicles (every 10th vehicle in the study) aimed to facilitate the flow of traffic by creating gaps that would allow as many vehicles as possible to move through. This was accomplished by having these vehicles voluntarily decelerate to a predetermined speed. The deceleration should not begin too close to the roundabout, as this approach does not yield the desired effect, and nor should it start too far away, as that would cause vehicles to queue behind and eliminate opportunities for vehicles on the yielding road to merge. This study found that beyond 60 to 80 m, further distance has little to no effect on the outcome, while the only parameter to have an influence is the percentage of velocity reduction. An optimal combination of variables was also identified. To determine this ideal combination, a genetic algorithm was employed with two objectives: maximizing the number of vehicles on the secondary road while minimizing the increase in travel time on the priority road. One question that arises is, "What should be prioritized in the optimization algorithm—number of vehicles or time?" It would be logical to assume that for peak traffic periods, most optimizations oriented towards traffic fluidity would require the prioritization of the number of vehicles on the yielding road passing over the roundabout versus the time required for vehicles on the priority road to clear the roundabout. This objective can be easily achieved by adjusting the weighting factors in the algorithm.

For the input data that we used, we observed an increase in the number of crossing vehicles for the yielding road ranging from 245.45% for model no. 10—an increase of 27 vehicles, up to 583.33% for model no. 6—an increase of 35 vehicles. This resulted in a mean value of 357.60% increase in the number of vehicles crossing the roundabout across all 10 models. The side effect was a minimal increase in crossing time for priority road vehicles, ranging from 0.12% for model no. 7 up to 1.39% for model no. 4. More specifically, the crossing time ranged from 171.8 s for model number 9 to 174.6 for model number 4.

We assumed that autonomous vehicles are fully aware of the simulated scenario, but the proposed optimization algorithm cannot be universally applied due to the lengthy simulation time and the requirement to know all initial parameters. As a result, we decided to impose default values for distance and speed reduction percentages. These input values can be implemented when autonomous vehicles detect traffic patterns similar to those described earlier. A key parameter is the distance between vehicles in both directions, which also indicates traffic volume. The selected values for these parameters were based on the averages from 10 optimization runs, where two weight factors were assigned—2 for the number of vehicles, and 1 for time. The optimized traffic results for models 1, 3, 5, 6, 8, and 9 showed an increase of over 300% in volume. Among these, model 6 performed the best, achieving a remarkable increase of over 550%. In contrast, models 2, 4, 7, and 10 had modest increases below 300%, with model 10 being the least effective. Additionally, vehicle crossing times on the prioritized road highlighted models 5 and 10 as the best performers, each experiencing an increase of less than 2 s. In opposition, model 7 had a longer increase, exceeding 3 s.

To summarize, the main contribution of this research is an optimization strategy designed to improve the efficiency of roundabouts by focusing on the speed and timing of speed reduction for autonomous vehicles entering the roundabouts. Key points include the following:

- The ten realistic baseline models used in this study demonstrate that the improvements made by the proposed algorithm significantly enhance traffic flow on roundabouts.
- The proposed strategy employed a multi-objective genetic algorithm in the baseline models and showed substantial improvements in traffic flow across all ten tested scenarios.
- Imposing optimized mean values for distance and speed reduction ratios enhances roundabout efficiency through better coordination of autonomous vehicles and without running long optimization algorithms.

Future research should consider traffic from multiple directions, the presence of pedestrians at crosswalks, and how distances between vehicles are not uniform in normal conditions.

5. Conclusions

This study presents an optimization strategy designed to enhance the efficiency of roundabouts by strategically coordinating the speed and timing of autonomous vehicles' deceleration as they approach. The research demonstrated that employing a multi-objective genetic algorithm significantly improves traffic flow across various models, with some achieving over 550% increases in the number of vehicles crossing from the yielding road. The proposed algorithm effectively balances the dual objectives of maximizing vehicles crossing the roundabout for the yielding road while minimizing delay on the priority road. Key findings indicate that carefully selected default values for distance and speed reduction can further optimize roundabout performance without running long optimization algorithms. This study highlights the potential of autonomous vehicle coordination to improve traffic at roundabouts, suggesting pathways for future research that could incorporate multi-directional traffic flows and more complex scenarios. Despite conducting our study using realistic data, they are subject to some limitations regarding the number of vehicles on both roads, the traffic conditions, the presence of other circulating vehicles that might have an impact on the traffic flow (heavy trucks, public transport, cyclists, emergency vehicles), and the visibility conditions. Several factors can significantly influence the effectiveness of the approach being examined. Reduced visibility conditions can lead to increased time gaps between vehicles, which subsequently reduces flow efficiency. Additionally, the presence of different types of vehicles may disrupt predictions due to the time and space required for maneuvering over roundabouts. Furthermore, the presence of cyclists and pedestrians can impact the prioritization of safety over traffic flow efficiency.

Nonetheless, in other suburban neighborhoods, similar traffic patterns emerge during peak hours, with drivers exhibiting predictable route choices. The results of this study can be easily adapted to these situations. The impact of the introduction of autonomous vehicles on people and traffic will be a strong one, and according to the latest predictions and estimations, this transformational change is close to occurring.

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