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DEVELOPING ROUTES USING HYBRID SIMULATIONS: PUBLIC TRANSPORT VS. BIKE SHARING

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Abstract
This study compares implementing a bicycle-sharing system with the current bus transport system in Belo Horizonte, Brazil. We developed a hybrid simulation model, combining Agent-Based Modelling and Discrete Event Simulation, using AnyLogic software. The model's environment was constructed with Geographic Information System (GIS) tools integrated into the software, enabling the mapping of urban routes and facilitating agent decision-making. Based on the validated and statistically verified model, we created nine scenarios to compare travel times between bicycles and public transport. The scenarios considered key variables such as average speed, number of users, weather conditions, and infrastructure quality. The results showed that bicycles offer a more efficient alternative for the final leg of travel, significantly reducing travel times. This research highlights the potential benefits of bicycle-sharing systems and provides valuable insights for decision-making in urban transport infrastructure planning.
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Key Words: Urban Mobility, Transport Infrastructure, Agent-Based Simulation, Discrete Event Simulation

1. INTRODUCTION

Mobility in urban environments involves moving to reach desired destinations using various modes of transport. It is essential for the sustainable development of cities and is necessary for activities such as commuting, professional tasks, personal errands, leisure, and more [1]. However, among the available modes of transport, the automobile has dominated globally since the 20th century. As a result, urban planning has often prioritised motor vehicles, leading to infrastructure that favours their circulation at the expense of alternatives like bicycles and public transport [2, 3]. This preference has led to several negative societal impacts, including congestion, pollution, traffic safety, driver stress, and economic consequences for cities [4].

To address this issue, Kagho et al. [3] highlight a significant increase in publications on mobility modelling using computer simulation. One of the key approaches is hybrid simulation (HS), which combines the strengths of discrete event simulation (DES) for modelling flows in production processes, such as bus systems and general traffic, with agent-based simulation (ABS), which captures the behaviour of individual vehicles, passengers, and entities influencing urban mobility. Additionally, Aziz et al. [5] note that ABS can be used to assess the impact of transport-related infrastructure, helping to improve planning and optimise resource allocation. These models simulate agents with sociodemographic traits, capturing complex transport interactions and providing insights for urban planning.

In this context, this article aims to develop and apply a hybrid simulation model to analyse urban transport systems by comparing travel times on public bus routes with those of shared bicycles in Belo Horizonte, Brazil. The specific objectives are to: model the HS of the city's central region with defined origin and destination points using AnyLogic software; validate the bicycle-sharing model for the studied urban area; and compare travel times using scenarios with variations in the speed of public transport and bicycles.

The study's relevance is supported by 400 % rise in the number of bicycles across Latin America over the last decade. In Brazil, there are over 75 shared bicycle systems, representing about 33 % of all systems, with an average of 0.25 bicycle trips per person per day, one of the highest rates globally [6]. Another important aspect is the integration of cycle path networks with public transport systems, which benefits various social classes by encouraging travel for professional, educational, cultural, and leisure purposes. This integration promotes equal access while reducing public spending [7]. Furthermore, in [7, 8] it is emphasised that this mode of transport supports environmental, social, and economic sustainability and is linked to health benefits, such as reduced risks of heart disease, mortality, and cancer through physical activity.

In terms of computational modelling, in [9] the growing use of such theoretical and practical solutions in real-world environments is highlighted, including logistical considerations, as demonstrated in studies by [3, 5, 10-12], among others. Future research opportunities to optimise hybrid simulation in various settings are suggested in [10], while in [8] it is proposed using microsimulations for short routes involving different transport modes and in [13] the freight planning and policymaking in new studies for other new forms of transports services.

Given the benefits of shared bicycles and the value of simulation as an analytical tool, this research aims to contribute scientifically by developing a simulation model that supports decision-making for implementing shared bicycle infrastructure in large urban centres. Additionally, it seeks to create a replicable model that can be applied to various urban contexts, thereby expanding the approach's scope and usefulness. To achieve this, the study is organized into seven sections: introduction, theoretical review, research method, development of the computational model, validation and verification of the model, creation of scenarios, and conclusion. The text is related as an original scientific article using new applications of an already known theory and simulation technology.

2. LITERATURE REVIEW

2.1 Hybrid simulations

A model is an abstract and simplified representation of an existing or planned reality, reflecting a situation from the perspective of an individual or group [14, 15]. A simulation is the tangible manifestation of a model, typically implemented through a computer programme that provides insights into the system or application being studied. In essence, simulation involves creating a model of a real system and conducting experiments with it [14].

Several approaches are available in simulation, including Dynamic Systems, Continuous Simulation, Discrete Event Simulation (DES), and Agent-Based Simulation (ABS), among others. Hybrid Simulation (HS) combines multiple techniques to model and analyse complex systems. It integrates different types of simulation models, offering a comprehensive and accurate view of system behaviour, and enabling the exploration of various scenarios, policy testing, and decision-making based on simulation results [16]. The literature demonstrates that HS has been applied in many fields, including transport, logistics, engineering, economics, and social sciences. It is used to model complex real-world systems, such as transport networks, supply chains, and urban environments [13, 17, 18].

In this article, Hybrid Simulation (HS) was implemented by combining the steps of Discrete Event Simulation (DES) and Agent-Based Simulation (ABS). In a DES, the process starts with an event triggered by a change in resource or element states at a discrete point in time [19]. In contrast, ABS is characterised by autonomous agents that interact with both their environment and other agents to achieve specific goals [12, 19, 20]. Moreover, Sena et al. [10] emphasise that working with human elements requires more than just logical, analytical, and computational knowledge. Psychological, cultural, and other factors significantly influence human behaviour, making hybrid simulation particularly suitable for this study.

2.2 Shared bikes

Shared mobility refers to the shared use of vehicles, often associated with first- or last mile connections. Common examples include e-scooters, e-bikes, and autonomous cars [3, 21]. Shared bicycles allow users to pick up a bike at a designated station and return it at another, facilitating transport connections.

In the literature, studies can be listed on the use or sharing of bicycles. An example is in [22]; they began their studies with an article on multimodal simulation with sharing of bicycles and other mobility equipment in a generic city in China, and they complemented the studies, indicating in their simulation with the MATSim software, how the use of smartphones affects such a network for reservation or information on where the equipment to be shared would be. Yang et al. [23] sought to study the impact of bicycle sharing on a public urban transport network also in China through mathematical and geographical means, while in [24] it is verified the use of this type of system, but without docks or docking stations, in the city of Singapore.

Bicycle-sharing systems offer a compelling alternative due to their speed and efficiency, providing an affordable solution for last mile trips [25]. They contribute to urban sustainability by reducing dependence on cars for short distances, supporting first and last mile trips for both individuals and parcel delivery, and complementing existing mobility solutions [8].

According to [26], the main barriers identified in studies relate to infrastructure, including the lack of cycling lanes and bicycle stands, uneven terrain, and insufficient signage. Additionally, weather conditions such as rain and fog are noted as obstacles. Conversely, health and economic benefits are cited as the primary incentives for cycling.

3. RESEARCH METHOD

This study is classified as descriptive applied research with a practical focus, employing a qualitative-quantitative approach. This allows for a detailed qualitative description of the actions while using quantitative data to draw conclusions and achieve the objectives [27].

The research method follows the modelling and simulation framework of Bertrand and Fransoo [15], which is defined as normative and axiomatic. The steps of the research are: conceptualizing the objectives, characterizing the object of study, determining the study variables, developing the conceptual model, translating it into a computational format using AnyLogic software (as used by Barbieri et al. [12]), validating it using Minitab software, and conducting experiments via scenario testing. For the Agent-Based Simulation (ABS) classification, the study is considered individual, as the agents' behaviours are prescribed by code with limited interactions and no adaptability, as described by Macal [28].

Regarding the steps followed in this study, we adhered to the ODD protocol laid out in [29]. This handy protocol breaks things down into three stages for constructing the article:

1. **Overview** – We began by defining the model’s objective, setting up the state variables, figuring out the agents' scale, and mapping out how the agents would fit into the model.
2. **Design Concepts** – This is where we determined how the agents interact, adapt, and evolve within the model (basically, ensuring they are not merely interacting aimlessly).
3. **Detailing** – Finally, we outlined how the model starts, what inputs it needs, and the basic equations and functions that keep everything ticking.

4. DEVELOPING THE MODEL

4.1 Overview

The goal of this study is to simulate, through a hybrid simulation (HS), a system that compares the use of public buses with the alternative of shared bicycles. This simulation aims to support decision-making regarding the implementation and development of public infrastructure for this mode of transport. The model is built on the interactions between the agents within the system and their respective characteristics.

To achieve this, the model incorporates three types of agents: the user, the bus, and the bicycle. The simulation environment is based on the Geographic Information System (GIS) of the central region of Belo Horizonte, Brazil, as illustrated in Fig. 1. The two green points in the figure represent the users' origins, which are the metro stations that lead to the city centre, with a large volume of people, the object of study of this article. The four red dots are centroid points of great movement of people, in the studied area, and are identified as the destination points. The decisions made by the user agents follow a set of criteria, which are detailed in section 4.3.

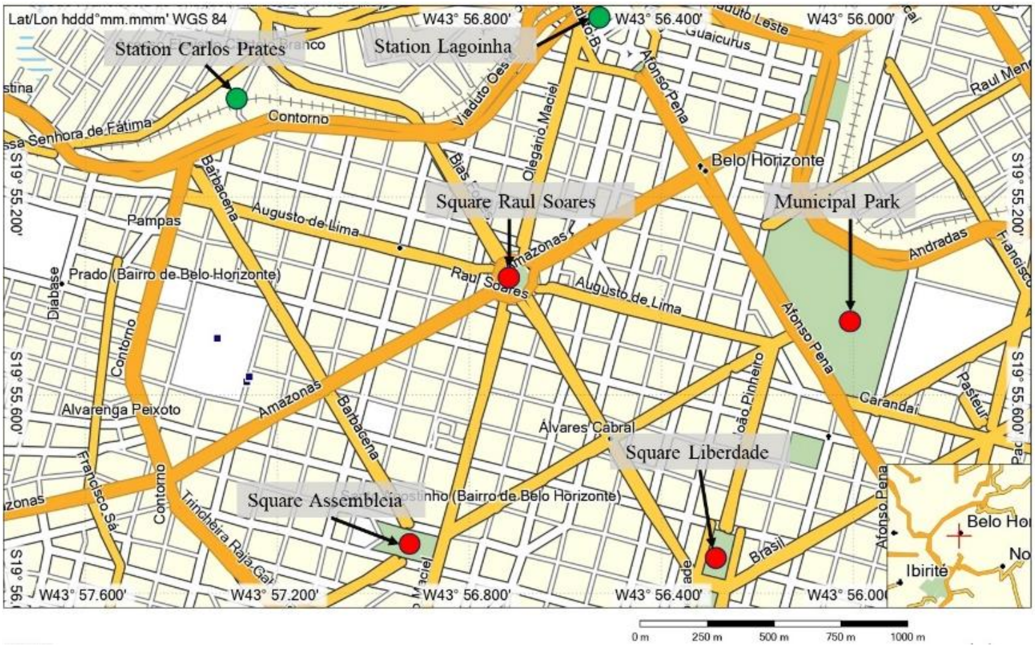


Figure 1: Map of the simulated region with origin (green) and destination (red) locations.

The simulation compares the behaviour of bike-sharing and bus systems from departure at the origin to arrival at the destination. The model distributes 8,022 users along fixed routes, with each user selecting a mode of transport. Once a decision is made, users follow the flow of the chosen transport and are removed from the system upon reaching their destination. Data are then recorded for analysis. Fig. 2 presents a flow diagram of the entire process, including the three agents.

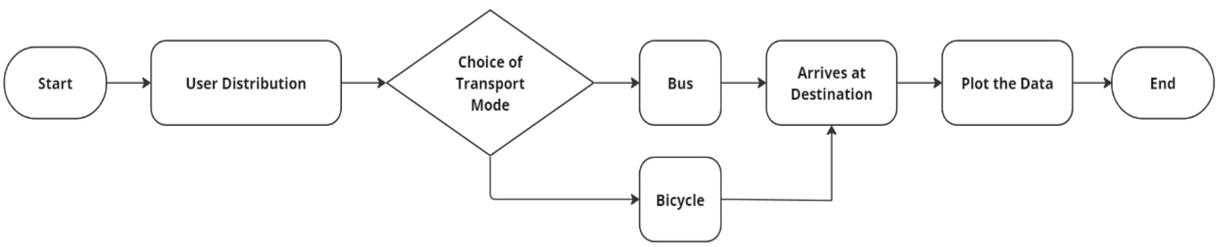


Figure 2: Model process overview flow diagram.

The first step involves distributing the agents across the model, with 25 % of the users assigned to each destination point, totalling 8,022 entries. In the decision block, the user agent selects a transport mode. After making this choice, the user follows the flow for the selected transport, as shown in Fig. 2. Upon reaching their destination, agents are removed from the system, and the data are collected for future analysis.

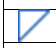
4.2 Design concepts

In this stage, the project concepts are presented according to the ODD Protocol. While the protocol includes eleven subitems, as outlined by Grimm et al. [29], not all were necessary for the construction of this model. The applicable subitems are as follows:

- **Objectives**: The agents replicate the behaviours of each system to support decision-making;
- **Adaptation**: The agents' decisions are influenced by individual preferences, dynamically adapting to transport choices;
- **Anticipation**: The agents cannot determine which stage of the process they are in;
- **Communication**: The agents interact with one another; at one stage, users acquire characteristics of the selected agent, forming a combined agent;
- **Coordination**: The model does not consider collective behaviour, as agents are unaware of the actions of others;
- **Selection**: The agents randomly select different behavioural options based on pre-determined characteristics.

With these design elements in place, the computational model was developed using AnyLogic software, which enables the integration of Discrete Event Simulation (DES) and Agent-Based Simulation (ABS) into a Hybrid Simulation (HS). The GIS tool within the software was used to visualise the study region, incorporating the coordinates for origin and destination points via point nodes. The action blocks, summarised in Table I, outline their use in the model, allowing the development of the process flow shown in Fig. 3.

Table I: Icon and description of the action blocks of the computational model.

Icon	Name	Function description
	Source	Arrival of agents at the model.
	Sink	Completion of the process flow with the disposal of agents.
	Queue	Queues of agents during the production process.
	SelectOutput	Routes the agent to one of the exit ports, depending on the condition.
	SelectOutput5	Routes incoming agents to one of five output ports, depending on conditions (probabilistic or deterministic).
	Combine	Wait for two agents, then produce a new agent from them.
	Assembler	Brings together a certain number of agents from multiple sources (5 or less) into a single agent, generating a batch.
	MoveTo	Moves an agent from its current location to a new location.
	Seize	Grabs the number of units of the specified resource required by the agent.
	ResourceTaskStart	Defines the start of the flowchart by modelling the task process for resource units (usually a resource preparation process).
	Enter	Inserts agents created elsewhere in the flowchart.
	TimeMeasureStart	TimeMeasureStart as well as TimeMeasureEnd make up a pair of blocks measuring the time that agents spend between them, such as "time in system", "dwell time", etc.
	TimeMeasureEnd	TimeMeasureEnd as well as TimeMeasureStart make up a pair of blocks measuring the time that agents spend between them.

The steps for Discrete Event Simulation (DES) in the computer system are outlined below, as illustrated in Fig. 3:

- **Step 1**: The 'user' agents are introduced into the system;
- **Step 2**: The SelectOutput mechanism evenly distributes the user population across the four available destination options;
- **Step 3**: On each route, the user decides on the destination and transport mode based on pre-determined criteria, as shown in Fig. 4;
- **Step 4**: The 'bicycle' agents are introduced into the system;
- **Step 5**: The 'bus' agents are introduced into the system;

- **Steps 6 and 7**: For buses, waiting time is recorded between these points using the timeMeasureStart and timeMeasureEnd tools;
- **Steps 8 and 9**: Bus travel time is measured between these points;
- **Steps 10 and 11**: For bicycles, travel time is recorded using timeMeasureStart and timeMeasureEnd between these points;
- **Steps 12 and 13**: The agents are moved from their current location to the desired destination using the GIS point-marking tools available in AnyLogic.

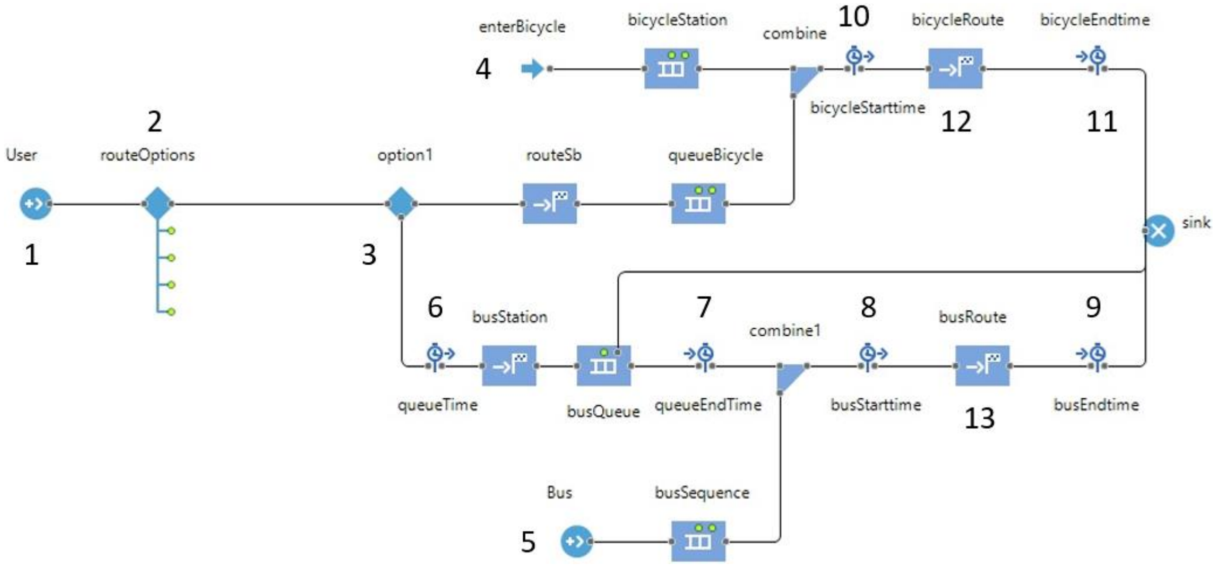


Figure 3: Process flowchart and model interactions.

4.3 Detailing

The decisions made by the user agents are based on several criteria: whether to cycle or not, weather conditions (sun or rain), and individual preference for cycling. These decisions are entered at point 3 of Fig. 3 and are programmed using the AnyLogic software with Java code shown in Fig. 4.

In short, this code starts by defining the three strings of conditions (weather, whether to travel and preference for travel by bicycle), as per lines 1 to 3. The conditions are made random and Boolean for each agent's definition (Yes or No) as per lines 5 to 8. After this, the sequences of options are created between lines in the programming code 10 to 29: if the weather is sunny (dry) and the agent wants to cycle, then the agent selects the bicycle option over the bus; if the weather is sunny (dry) and the agent does not want to cycle, the agent is made to choose randomly whether he will travel by bus or by bicycle; if it is raining and the agent does not want to cycle, the agent will opt for the bus; if it is raining and the agent wants to cycle, the agent is prompted to choose randomly whether he will travel by bus or by bicycle. After this choice, the chosen travel option is presented during the simulation as illustrated in lines 30 and 31.

The input values for the variables considered in the model were entered to begin the simulation. Table II lists these variables, along with their initial parameters, possible variations, and corresponding descriptions. In section 6, the variations in each initialisation will be tested to assess the model scenarios.

5. VERIFICATIONS AND VALIDATIONS

Following the approach given in [15, 30], once the model was built, checks were conducted to identify any inconsistencies, such as bugs or coding errors. The strategy involved testing and analysing the execution summaries until no further inconsistencies were found.

```
String wether = comboClima.getValue( );
String[ ] wantsToGo = {“no”, “yes”};
String[ ] preference = {“doesNotPeda”, “pedals”};

boolean choice = false;
Random random = new Random( );
String randomWantsToGo = wantsToGo[random.nextInt(wantsToGo.lenght)];
String randomPreference = preference[random.nextInt(preference.lenght)];

    if (weather.equals(“Sunny”) && randomPreference.equals(“pedals”)) {
        choice = true;
    }

    if (weather.equals(“Sunny”) && randomPreference.equals(“doesNotPedal”)) {
        if (randomWantsToGo.equals(“yes”)) {
            choice = true;
        } else {
            choice = false;
        }
    } else if (weather.equals(“Rainy”) && randomPreference.equals(“doesNotPedal”)) {
        choice = false;
    }

    if (weather.equals(“Rainy”) && randomPreference.equals(“pedals”)) {
        if (randomWantsToGo.equals(“yes”)) {
            choice = true;
        } else {
            choice = false;
        }
    }

    System.out.println(“Generated values:_” + choice);
    Return choice;
```

Figure 4: Decision-making code.

Table II: Initial values of the model.

Variable	Initial value	Possible variation	Description
Number of users	8,022	Value corresponding to the reality of the simulation location	Sampling number of users.
Bus waiting time	24 minutes (local average)	Value corresponding to the reality of the simulation location	Sampling bus waiting times
Bus speed	10 km/h	Varies between 10 km/h and 45 km/h	Values vary according to scenarios.
Bike speed	5 km/h	Varies between 5 km/h and 25 km/h	Field and average data.
Walking speed	3.6 km/h	N/A	Field and average data.
Climate	Sun	Rain	Depending on the desired scenario.
Data collection	Real time	N/A	Times are collected in real time and plotted on a graph.
Presentation of results	Total travel time	N/A	Buses and bicycles are presented at each completion.

For model validation, the framework proposed in [30, 31] was applied, comparing real data with the data generated by the simulation, with a focus on travel times. The route between

Lagoinha station and Municipal Park (shown in Fig. 1 as the origin and destination points on the map) was selected for validation, as it had the largest dataset available. The simulation generated data for the same route, and these were compared with the real data using a natural logarithm calculation.

The Anderson-Darling normality test was applied to both data sets using MiniTab software. For the values collected in the field, a *p*-value of 0.111 was obtained, and for the simulated values, a *p*-value of 0.246. In both cases, since the *p*-value was greater than 0.05, null hypothesis could not be accepted with 95 % confidence, indicating that the datasets are consistent with normality, as dictated by Montgomery and Runger [31].

In the next step, Minitab's *F* test was used to compare the two samples, as was done in the work of Lopes et al. [32], obtaining a *p*-value of 0.806. Analysing according to [31], it is noted that the significance level was greater than 0.05 (95 % confidence), demonstrating that the values are statistically similar. The results were also subsequently validated using the Smith-Satterthwaite method, which was substituted with Minitab's *T*-test, obtaining a *p*-value of 0.068, corroborating that the means of the simulated and real data are statistically similar.

6. CREATING THE SCENARIOS AND RESULTS

As the final step of the axiomatic normative model proposed in [15, 30], experiments were conducted for the simulation model to support decision-making. In this study, the experiments were translated into scenarios that reflect real-world situations in a virtual environment.

The simulations were scheduled over five business days (Monday to Friday) and focused on both the shared cycling system (the primary focus of this study) and the public bus transport system (used for comparison). The model considered a population of 8,022 users, evenly distributed across the different routes. The interval between buses was fixed at 24 minutes.

The speeds varied between the bus and bicycle agents, as each individual could encounter different circumstances, resulting in a broad range of travel times. This setup was designed to evaluate the urban infrastructure for both transport modes, based on the empirical experience of the authors. However, to assist in defining the speed variations, the works of Yang et al. [23] and Shen et al. [24] were also used, which, respectively, adopted averages of 12.5 km/h and 15 km/h for bicycles. In this article, a speed range of 10 to 25 km/h was used, in steps of 5 km/h. For the speed of buses, Yang et al. [23] used an average of 20 km/h, whereas in this article, it was varied within a range of 17 to 30 km/h.

With four standardised destination routes across five working days, a total of 60 time output variables were generated for each set of conditions: one for the bus travel time, one for the bicycle travel time, and one for waiting time without selecting a mode. Not all possible variations were simulated; the scenario design demonstrated is detailed in Table III.

Table III: Input values of speed parameters (in km/h) for each scenario C.

Scenario	Bus velocity	Bike velocity
C1	17	10
C2	25	15
C3	17	20
C4	15	10
C5	10	25

Scenario	Bus velocity	Bike velocity
C6	15	20
C7	20	15
C8	25	10
C9	30	5

We calculated the average time spent by users on both bus and bicycle modes for each of the four destination points (routes) across the nine scenarios. We then presented the results graphically, with time in minutes on the y-axis and the scenarios on the x-axis, as shown in Fig. 5.

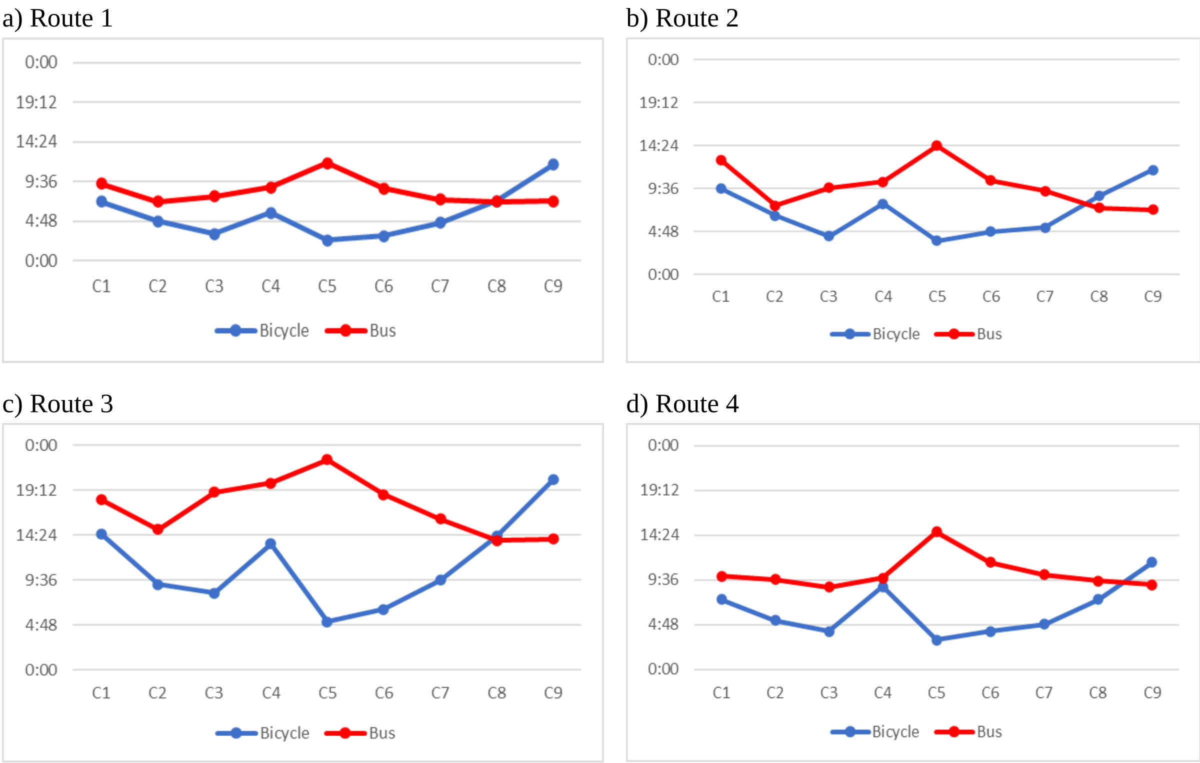


Figure 5: Travel times by bike and by bus in each scenario on each route.

Analysing Route 1, we observed that travel times vary between buses and bicycles across different scenarios. Buses perform better in scenarios C2, C8, and C9, while bicycles are faster in C5. In scenarios C8 and C9, where buses have a speed advantage, bicycles take longer but still offer benefits such as no waiting time and the ability to manoeuvre through dense traffic. On the second route, similar to Route 1, buses outperform in C2, C8, and C9, while bicycles are quicker in C5. Despite their slower speeds in these scenarios, bicycles still present a comparative advantage in overall travel time.

On Route 3, travel times decrease compared to the previous routes. Buses perform better in C9, while bicycles are faster in C5, with an increase in travel time only observed in C9. Route 4 shows a similar pattern to Route 3, where buses outperform in C9 and bicycles are faster in C5, with travel times increasing only in C9.

Across all routes, bicycles generally have an advantage in terms of travel time, especially in scenarios that favour their fluidity. Even in the final scenarios, where buses have a significant speed advantage, bicycles remain a viable option for short distances due to the lack of waiting time and their ability to navigate through dense traffic.

The detailed results show that shared bicycles outperformed public transport in efficiency in travel time, even under challenging conditions such as congestion, with time savings ranging from 14 % to 61 %, as shown in Fig. 5. In scenarios with a greater speed difference between the transport modes (scenarios 8 and 9 on each route), bicycles performed worse. This lower performance is explained by infrastructure favouring bus transport, resulting in travel time losses of up to 50 %. However, when the infrastructure supported both modes equally or favoured bicycles (in scenarios with higher bicycle speeds), travel time savings reached up to 79 %.

The analysis of route times revealed an increasing trend in travel times for bicycles as their speed decreased, with a loss of efficiency of up to 82 % in the least favourable scenario. These findings highlight the necessity for investment in cycling infrastructure to promote faster, more sustainable and efficient urban mobility.

7. CONCLUSION

The objective of this study was to develop and apply a hybrid simulation model to analyse urban transport systems, comparing shared bicycles with bus transport. This objective was successfully achieved by following the research method steps and constructing the model using AnyLogic software.

The study focused on two origin points and four destination points within the central region of Belo Horizonte, Brazil. The GIS tool integrated into AnyLogic was used to simulate the movement and flow of agents along the actual routes. This setup allowed us to achieve the second specific objective, which involved using Minitab software to conduct normality and paired tests, verifying and validating the computational model. These tests produced positive results, statistically confirming that the virtual model accurately represents the real-world environment.

For the final specific objective of the study, nine scenarios were generated in the validated model to evaluate the speed of both the current urban bus system and bicycle routes. Four routes were analysed within the study area, and the travel times of the public bus system were compared with those of the bike-sharing system. It was observed that the speed of each mode significantly influenced travel time, with faster speeds reducing overall travel times. Since the experiment focused on changes to urban infrastructure, such as dedicated bus lanes or cycling lanes, the results showed a significant percentage improvement for shorter distances when investing in bike-sharing systems. This indicates that as travel speed increases, the efficiency of the area's traffic system improves.

During on-site data collection, the lack of infrastructure on some routes was noted, which posed challenges for both data collection and general travel within the city. The findings highlights the necessity of ensuring appropriate infrastructure before implementing a bike-sharing system. This study also highlights the importance of on-site data collection for validating the model and gaining a deeper understanding of the city's unique characteristics.

One limitation of the model is that it does not account for road elevation, suggesting routes based purely on distance and permissible directions. As a result, it may propose routes that are not ideal for comfortable cycling journeys. Incorporating this variable into the model would require a detailed study of the effort required to navigate inclines in the city, which is suggested for future research.

In conclusion, this study finds that the inclusion of a shared cycling system as an alternative for short-distance urban transport is a viable option. Such a system offers several advantages, including reduced waiting and travel times, decreased pollution and urban congestion, improved infrastructure, and health benefits for users. Therefore, we recommend that Belo Horizonte invest in improving its bicycle infrastructure and promoting the use of this sustainable mode of transport.

The scientific contribution of this research is highlighted, bringing to light the themes of transport by different modes (bicycles and buses) in a hybrid simulation with the AnyLogic software. It corroborates the literature of the area also in the use of the ODD protocol as a method, obtaining good results and aiding the virtual development of the emulation. Finally, the comprehensive explanation of the computational model's construction with the diagrams and lines of code can help other researchers in similar studies.

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