A simulation model for credit schemes and sustainable behaviour

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***Abstract*—This study presents a simulation model designed to analyse the impact of employee transportation choices on sustainability, with a focus on carbon emissions and cost efficiency. Incorporating real route data and various scenarios, the model evaluates commuting behaviours across different transport options while considering the roles of both workers and companies. Companies are analysed with and without carbon emission budgets and incentive policies, highlighting their adaptation strategies to promote sustainability. The simulation, implemented in Python using tools such as Mesa and OSMnx, features real-time interactive visualizations, enabling an intuitive exploration of the results. This approach provides valuable insights into the relationship between incentive policies, worker behaviour, and environmental outcomes.**

I. Introduction

Employee commuting is a major contributor to urban traffic congestion and carbon emissions, presenting significant challenges to sustainability efforts. In response, organizations have implemented various strategies to promote alternatives to private car usage, such as public transit, cycling, and carpooling. Among these strategies, credit schemes have emerged as a possible approach, providing incentives for employees to adopt more sustainable commuting practices. By offering points, subsidies, or other rewards, these schemes aim to encourage behavioural shifts towards environmentally friendly transport modes while addressing economic and convenience concerns.

However, while credit schemes are promising tools to foster sustainable behaviours, modelling their precise effects on transport choices presents several challenges. The impact of a credit scheme on an individual's decisions is inherently subjective and depends on factors like personal preferences, economic priorities, and accessibility to alternative transport modes. Capturing this complexity in a simulation requires extensive data from practical studies, which is not feasible in our case. Otherwise, our views and assumptions when modelling each credit scheme would directly determine their performance in the simulation, thereby undermining the purpose of testing and comparing their outcomes objectively.

Given these constraints, we chose not to model credit schemes directly. Instead, we assumed that transport choices are influenced by unspecified interventions that alter behaviour, the credit schemes. By doing so, we can focus on analysing the consequences of these changes, particularly their impact on the carbon footprint.

In summary, this study aims to understand the implications of altering transport choices for employees commuting to work. Instead of prescribing a specific mechanism, like a credit scheme, that affects these choices in a subjective manner, our simulation investigates how changes in the choices impact cost and environmental metrics.

The key contributions of this study include:

- A flexible simulation framework for evaluating transport choice alterations;
- Insights into the effects of such changes on sustainability;
- Recommendations for future sustainable transport policy development.

II. Methodology

A simulation model was developed to assess the impact of altered transport choices, incorporating real-world commuting data to ensure relevance and accuracy. The framework evaluates the system under various scenarios, enabling a comprehensive analysis of potential outcomes. The model's structure and components are detailed in Section II-A.

A. Simulation Framework

In this study, we adopt a "what-if" analysis framework to explore the effects of altered transport choices on sustainability. By employing both **prescriptive** and **speculative** simulation models, we can identify the necessary system transformations to achieve sustainable outcomes and evaluate hypothetical policies under various configurations. This approach provides a structured methodology to analyse the consequences of transport behaviours.

- **Speculative simulation model:** In the absence of detailed empirical data, a speculative simulation model was devised to explore hypothetical scenarios. This model enables the analysis of how different operational policies and system configurations might perform in untested conditions, providing valuable insights into potential outcomes and areas of improvement;
- **Prescriptive simulation model:** To evaluate specific system interventions—such as adjustments to carbon dioxide (CO_2) budgets per employee—a prescriptive simulation model was developed. This model focuses on recommending actionable strategies to achieve predefined sustainability goals, ensuring a targeted approach to decision-making and policy testing.

1) Variables: Understanding the variables involved in the simulation is critical to interpreting its outcomes. Here, we outline the key input and output variables used in the model. Input variables represent factors that can be adjusted to shape the simulation environment, while output variables capture the results of the simulation, providing insights into sustainability and cost-efficiency. The complete meaning behind each variable is clarified later, in Section II-B.

Input Variables:

- Number of workers per company;
- Number of companies with each policy;
- Budget of CO_2 emissions;
- Transport choices distribution.

Output Variables:

- Average CO_2 per company type;
- CO_2 emissions per employee;
- Total CO_2 emissions;
- Average transport costs.

2) Data requirements: The accuracy and relevance of the simulation depend on well-defined data inputs. This section describes the critical data elements used in the model, including emissions and cost data for transportation methods and real-world street network information. These data points were carefully selected and standardised to ensure consistency and transparency in the simulation results.

- **The approximate CO_2 emission in g/km of cars and electric scooters:** This is important to calculate the CO_2 emissions of each worker. We assumed that all workers have access to the same car model and electric scooter for more clarity within our results. The values we used were:
  - Emissions of CO_2 for cars: 250 g/km [1];
  - Emissions of CO_2 for electric scooters: 67 g/km [1].
- **The approximate monetary cost in €/km of cars and electric scooters:** This information is relevant to calculate the transportation costs for each employee. We used the same approach here as in calculating the emissions of cars and electric scooters. The values considered were as follows:
  - **Overall consume of cars:** 5.0 L/100km;
  - **Price of gasoline:** 1.70 €/L;
  - **Overall consume of electric scooters:** 9 kwh/km;
  - **Overall price to charge the electric scooters:** 0.312 €/kwh.
- **Graph networks of the streets around FEUP (Faculty of Engineering of the University of Porto):** extracted with the Python library OSMnx [2]. This allowed us to run the simulation in a real environment, providing more accuracy, precision and coherency.

*3) **Performance metrics**:* To evaluate the effectiveness of the simulation and compare different scenarios, we established a set of performance metrics. These metrics measure key outcomes such as carbon emissions, budget efficiency, and the cost-benefit balance for workers. By focusing on these metrics, the simulation provides actionable insights into the sustainability and practicality of commuting behaviours and policies.

- CO_2 emissions;
- Efficiency of the CO_2 budget cap value;
- Cost-benefit to the workers.

*4) **Scenarios**:* To evaluate the impact of transport behaviours and assess the effectiveness of various interventions, we developed multiple simulation scenarios. These scenarios build progressively on one another, introducing increasing complexity and incorporating key factors such as sustainability initiatives and environmental constraints. Each scenario allows for a focused analysis of specific aspects of commuting behaviour, providing insights into how individual and organisational choices interact to influence sustainability outcomes. All scenarios are based on specific assumptions, which are thoroughly explained in Section II-B.

a) Base Scenario: models a simplified commute where workers select their transportation method solely based on the path distance between their home and job.

b) Scenario 1: builds upon the base scenario by introducing a new element: sustainability-conscious companies. While some workers and companies continue to operate as in the base scenario, a subset of companies now prioritise sustainability. This means that employees within these specific companies will likely favour more eco-friendly transportation options.

c) Scenario 2: further expands our model by incorporating companies with varying CO_2 emission budget caps. These companies introduce a new dimension of constrained decision-making. While distance remains a factor, these companies now balance their employees' commute preferences with their environmental targets. They adjust their employees' sustainability based on the difference between the CO_2 emission budget and the actual CO_2 emissions, essentially simulating the application of different credit schemes.

B. *Implementation Details*

This section outlines the tools, methods, and techniques used to develop and execute the simulation model. The implementation focuses on accurately simulating transport choices and their sustainability impacts, using modern programming frameworks. Key aspects include simulation tools, graph structure, agents' behaviour, and visualisation methods. Additionally, the assumptions and approximations that guide the simulation are clearly outlined to ensure transparency and clarity.

The complete implementation is available on a GitHub Repository[1].

*1) **Simulation Tools**:* The simulation was implemented in Python, chosen for its versatility and robust ecosystem of libraries suited for modelling and data analysis. The following libraries were central to the development:

- **Mesa**: Used for building and running the agent-based simulation. Mesa's modularity and flexibility made it ideal for simulating complex systems with multiple interacting entities [3];
- **OSMnx**: Essential for loading and handling graph data, including street networks. It allowed for seamless integration of real-world geographic data [2];
- **Solara**: Enabled interactive and dynamic visualisations of the simulation, offering real-time feedback and flexibility.
- **Additional Libraries**: Libraries like pandas and matplotlib were used for handling data, generating plots, and enhancing overall analysis capabilities.

*2) **Assumptions and approximations**:* To maintain a balance between complexity and realism, we made several assumptions and approximations while modelling and building the simulation. These decisions were guided by the goal of achieving a manageable scope while preserving the accuracy of key system dynamics.

One significant assumption relates to **transport choices**. Workers are limited to four options: car, bicycle, electric scooter, and walking. While public transport plays a crucial role in real-world commuting, it was excluded from this model to avoid unnecessary complexity or oversimplifications. Incorporating public transports would require detailed data on transport locations, schedules, and possible secondary connections, such as combining walking or cycling with bus or train rides. Moreover, public transport availability often varies by time of day, adding another layer of complexity. While some of these factors could be well approximated, the integration of public transports into the model would significantly increase its complexity without a proportional improvement in accuracy. On the other hand, if we make too many simplifications to public transports, it would lead to a great loss of accuracy. For instance, relaxing availability greatly increases the appeal of public transports, since availability is one very relevant negative side of relying on this transport method.

Another simplification concerns the **geographic distribution** of homes and workplaces. Workers' home locations are assigned randomly across the total graph bounding box, whereas companies are placed within a smaller bounding box near the graph's centre. This approach ensures a realistic spatial distribution while simplifying data requirements. Additionally, workers are assigned to the nearest graph node to their randomly generated home location, with the distance to that node considered as walking distance. This assumption simplifies the representation of home-to-node connectivity.

We also assume that all companies have the same **number of employees**. This uniformity facilitates direct comparisons between companies and simplifies the analysis of their CO_2 budgets.

The environmental impact of transport choices is approximated by assuming **constant CO_2 emissions per kilometre** for each mode of transport. These values differ only by transport type (e.g., cars vs. bicycles), meaning all vehicles within a category are treated as identical. Similarly, the monetary costs associated with each mode of transport are assumed to be constant and category-specific.

An additional assumption is the **absence of traffic congestion**. Travel times are based solely on the shortest path distance for each transport choice, and workers select their transport mode accordingly. This simplification eliminates the need to model dynamic traffic conditions while maintaining a focus on the sustainability impact of transport behaviours.

In fact, we approximate the **distribution of transport mode choices** based on the computed shortest paths for each worker. This allows us to simplify the decision-making process while ensuring that transport selections remain consistent with the underlying graph structure.

In summary, by making these assumptions, we were able to streamline the simulation while focusing on the primary objective: analyzing the sustainability impact of different transport choice behaviours.

*3) **Graph Structure**:* Forms the backbone of the simulation, representing the physical environment of the employees' commuting routes. The graphs were obtained using OSMnx, leveraging real-world data with the following specifications:

- **Graph Creation**: Graphs were generated for three transport modes—drive, bike, and walk—within a bounding box of 5 km around FEUP (10 km by 10 km). These distinct graphs ensure that transport-specific constraints are respected, adding realism to the model (e.g., driving is not possible on pedestrian-only paths). In addition, we defined that electric scooters can move only on the "bike" graph.
- **Home and workplace assigment**:
  - Companies: Positioned randomly within a small bounding box (1 km) around the centre of the graph;
  - Employees: Assigned random home locations throughout the graph, simulating realistic urban distributions.
- **Path Calculation**: For each worker and graph type, the shortest paths from home to work (and back) are computed using OSMnx. This approach ensures that the simulation reflects real-world commuting distances.

*4) **Agent behaviour**:* Agents in the simulation are modelled as workers and companies, each with specific roles and behaviours:

- **Workers**:

[1] https://github.com/Minipoloalex/modelling-simulation/

TABLE I
SUSTAINABILITY FACTORS UNDER DIFFERENT POLICIES AND BUDGETS

Policy	Budget	Dynamically Modify Employees Sustainability	Initial Sustainability Factor
0	N/A	No	0 (const)
1	N/A	No	0.5 (const)
2	x1	Yes	0.5
3	x1.4	Yes	0.5
4	x0.6	Yes	0.5

  - Select a mode of transport each day based on the total commuting distance and a defined sustainability factor, which can vary throughout the simulation;
  - Navigate the graph one edge at a time, reflecting realistic movement patterns. This approach enhances visualisation and provides more fine-grained control, facilitating future improvements (e.g., traffic congestion).
- **Companies**:
  - Allocate a total CO_2 budget based on the number of employees, representing an organization's sustainability goals;
  - Influence workers' sustainability factors, simulating the effect of applying credit schemes or other behavioural incentives.

This agent-based approach allows for dynamic interactions between entities, highlighting the interdependence of individual and organizational choices.

Finally, as the scenarios definition indicate in Section II-A4, companies can have several different "policies". These policies indicate the behaviour the companies have towards their agents. We implemented 5 total policies, which are summarised in Table I.

The sustainability factor presented in the table affects the transport choice distribution, with higher values making it more probable that workers choose sustainable methods of transport. In addition, we defined the sustainability factor of employees of a specific company to be the same. Basically, this means that we assumed the credit scheme benefits are distributed evenly across the workers of a company.

Each company has an assigned CO_2 budget, which is defined as a factor of the base budget. The first two policies do not have an explicit budget, so we used the base budget to compare their results to others. The last three policies implement the adaptability of the sustainability factor of their employees based on meeting their the CO_2 budget. We can say that these companies are budget-aware and may create stronger credit schemes in order to meet their designated carbon footprint.

*5) **Visualisation**:* Effective visualisation is critical to understanding and analysing the simulation results. The implementation uses *Solara*[2], supported by Mesa's visualisation capabilities, to provide interactive, real-time insights.

[2]https://solara.dev/documentation

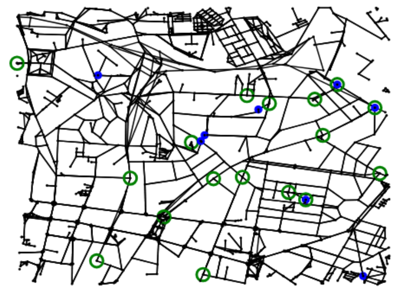

Fig. 1. Graph visualisation in the simulation web app: small blue dots represent companies and green circles represent workers

Our visualisation supports:

- **Parameter Modification**: Users can adjust model parameters, such as the number of workers per company and the number of companies of each type (defined in Table I);
- **Graph visualisation** (Fig. 1):
  - The graphs for different transport modes are merged for clarity, allowing the visualisation of agents moving through nodes in real time;
  - For larger graphs that are difficult to fully render, a partial view is displayed, focusing on the key area containing company locations.
- **Plot visualisation**: Real-time plots are generated during the simulation, showing key metrics such as the current CO_2 emissions compared to the assigned company budgets.

This visualisation approach not only enhances the interpretability of the simulation but also allows stakeholders to observe the immediate effects of parameter changes and interventions. Furthermore, during development, it provided a better understanding of any issues present in the simulations.

III. RESULTS

This section presents the outcomes of the simulation under various scenarios, providing insights into the sustainability impacts, cost-efficiency, and performance of different transport behaviours and company policies. Through detailed analysis, we explore the effects of altering input variables, such as company CO_2 budgets and transport choices, and evaluate their implications for overall carbon emissions and worker monetary costs.

Additionally, note that running simulations with a small number of workers per company or a limited number of companies results in unstable outcomes. In that case, these outcomes are heavily influenced by the sparse distribution of worker homes across the studied area.

A. *Base Scenario Outcomes*

The base scenario establishes a foundational understanding of transport choices and their environmental impact in a simplified commuting model. In this scenario, workers select

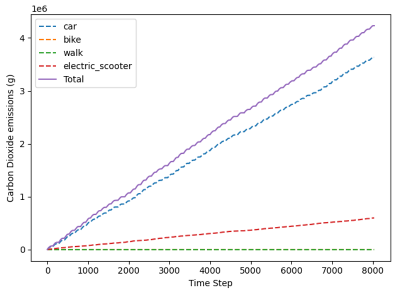

Fig. 2. Base Scenario: Total Carbon Dioxide (CO_2) Emissions for each transport

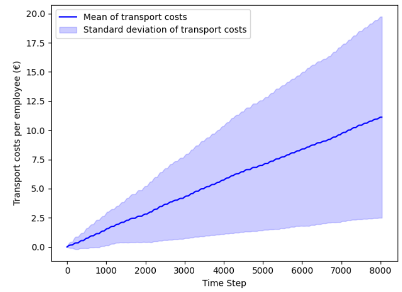

Fig. 4. Base Scenario: Mean and Standard Deviation of Transportation Costs per Employee

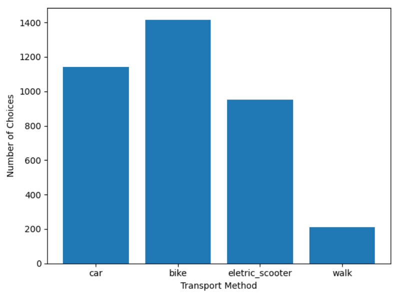

Fig. 3. Base Scenario: Total Transport Usage

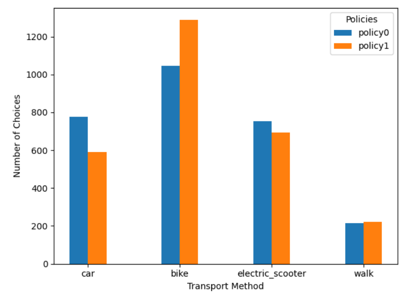

Fig. 5. Scenario 1: Total Transport Usage by Company Type

their transportation method solely based on the path distance between their home and workplace, without any incentives or interventions. The primary goal of this scenario is to observe the commuting patterns and resulting CO_2 emissions when individual choices are driven purely by convenience. So, in order to perform this initial analysis, we used 6 companies and a total of 20 workers per company.

The first plot, Fig. 2, illustrates a consistent rise in total emissions over time. While several modes of transport contribute to the increase in CO_2emissions, cars remain the most significant contributor throughout the simulation. This highlights the substantial environmental impact of car-centric commuting patterns, even within a model where distance is the primary factor in transport choice.

The **"Total Transport Usage"** bar chart in Fig. 3 reveals a different picture. Bikes are the most popular choice, followed by cars, and then electric scooters (while walking is the least preferred option). This suggests that while cars contribute the most to overall CO_2emissions, they are not the most frequently used mode of transport. This discrepancy could be attributed to the model's parameters, where distance is the sole determinant of transport choice, and factors like cost, travel time, and environmental impact are not considered.

Besides that, Fig. 4 indicates an upward trend in costs over time, with a notable increase in variability. This suggests that as time progresses, the average cost of commuting increases and there is a wider disparity in transport costs among employees. This trend could be related to the big preference for using cars instead of choosing much more sustainable and cheaper options.

In conclusion, the results demonstrate a complex interplay between cost, convenience, and environmental impact across different transport modes. While cars have the highest environmental cost, they are not the most frequently used. This highlights the limitations of a distance-based transport choice model and underscores the need for comprehensive policies and initiatives that incentivize sustainable transport choices while considering other factors, such as sustainable policies (implemented by the companies). So, this base scenario analysis provides a crucial foundation for understanding the impact of introducing sustainability-conscious companies and CO_2emission budgets in subsequent scenarios.

B. *Scenario 1 and Base Scenario Comparisons*

In this section, we analyse the effects of introducing sustainability-focused companies (Scenario 1) on transport behaviours and CO_2 emissions, comparing them to the base scenario. We decided to use 6 companies (3 of each type) and a total of 30 workers per company.

The **"Transport Usage"** bar chart for Scenario 1, Fig. 5, shows a noticeable shift towards more sustainable transport modes compared to the base scenario. As depicted in the figure, both `policy1` (representing sustainability-focused companies) and `policy0` (representing companies not focused on sustainability) show a preference for bikes. However, `policy1` exhibits a significantly higher usage of bikes and a lower reliance on cars compared to `policy0`. This highlights the effectiveness of sustainability-focused companies in promoting eco-friendly commuting choices.

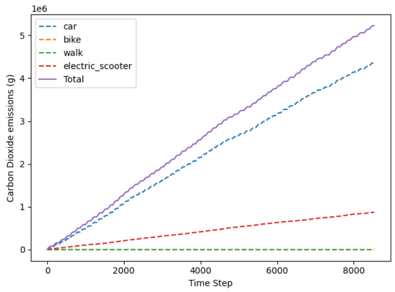

Fig. 6. Scenario 1: Total Carbon Dioxide (CO_2) Emissions for each transport

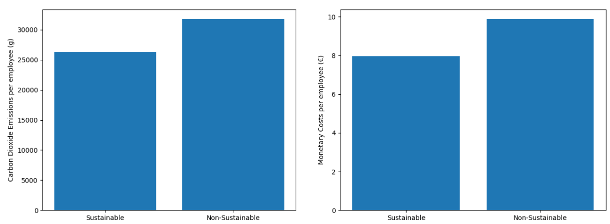

Fig. 7. Scenario 1: Comparison of Carbon Dioxide Emissions and Monetary Cost for sustainability-focused companies (`policy0`) and others (`policy1`)

Despite the shift towards sustainable transport, the graph **"Total CO_2 Emissions over time"** for scenario 1 (in Fig. 6) still shows an overall increase in emissions. This can be simply explained by the increase of workers present in the simulation. However, the rate of increase for cars in Scenario 1 is slightly lower compared to the base scenario, suggesting a mitigating effect from the introduction of sustainability-focused companies.

The **"Comparison of Emissions"** bar chart in Fig. 7 clearly demonstrates that sustainability-focused companies have significantly lower average CO_2 emissions per employee compared to non-sustainability-focused companies. Similarly, the **Comparison of Costs"** chart shows that transport costs are lower for employees in sustainability-focused companies.

To conclude, introducing sustainability-focused companies in Scenario 1 demonstrates a positive impact on transport behaviours and CO_2 emissions because employees are more likely to choose sustainable options, leading to lower average emissions and costs. However, to determine whether this decrease is significant or sufficient, we should establish a specific target or threshold, which is discussed in the next section.

C. Impact of CO_2 budget

As detailed in Section II, we implemented varying CO_2 budgets for companies in order to simulate how budget awareness impacts overall emissions. Budget-aware companies aim to keep their CO_2 emissions within predefined limits. To achieve this, we simulated the application of credit schemes that allow companies to adjust their employees' sustainability factors, influencing commuting behaviours and the resulting carbon footprint.

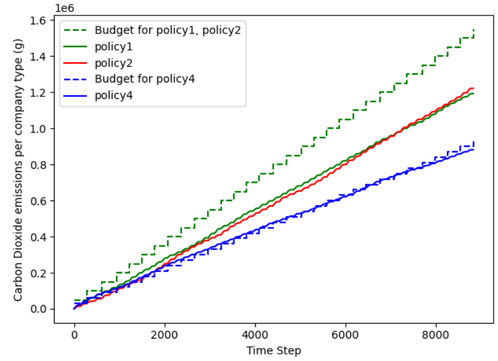

Fig. 8. Scenario 2: Comparison of average CO_2 emissions per company policy for budget-aware companies (`policy2` and `policy4`) and those without budget considerations (`policy1`)

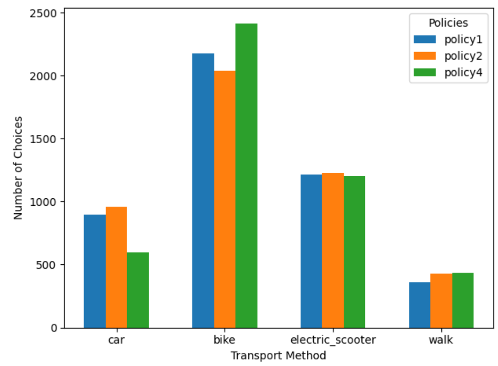

Fig. 9. Scenario 2: Total transport usage per company policy for budget-aware companies (`policy2` and `policy4`) and those without budget considerations (`policy1`)

Fig. 8 illustrates the comparison between companies with and without CO_2 budgets. This is the main focus of the second scenario, with the plot showing the overall CO_2 emissions per company type compared to their predefined budgets, over a whole month. Dashed lines represent the cumulative daily budgets, enabling both short-term (daily) and long-term (monthly) comparisons. The monthly comparison is particularly significant as it reflects the broader impact of these policies over time. Fig. 9 shows the total transport choices observed during the simulation for each company type.

In the simulation, companies with `policy1` represent employees who inherently prioritize sustainability, with a fixed sustainability factor of 0.5. For these companies, we do not explicitly define a CO_2 budget, but they are used as a baseline for comparison. On the other hand, companies with `policy2` actively manage their CO_2 footprint by adapting employee sustainability factors based on the gap between actual emissions and the desired budget. However, the impact of these adjustments appears minor, likely because emissions are strongly influenced by employees' home locations—factors that outweigh smaller adjustments to sustainability behaviour. In contrast, companies with `policy4` manage to precisely hit the designated CO_2 budget, without wasting any additional

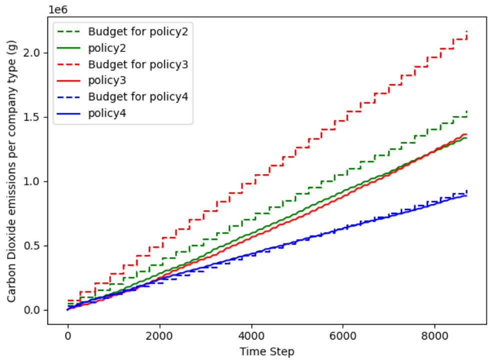

Fig. 10. Scenario 2: Comparison of average CO_2 emissions per company policy for different CO_2 budget values

resources. In Fig. 9, we can clearly see the improved sustainability of employees for this policy, with fewer workers relying on cars for transportation.

Furthermore, our approach to adapting CO_2 budgets is clearly shown in Fig. 10. We defined it such that companies emitting less CO_2 than their budget slightly reduce employee benefits and sustainability incentives. This ensures that unnecessary reductions in emissions, which may not be resource-efficient incentive-wise, are avoided. Conversely, companies exceeding their budget apply more stringent measures to bring emissions in line with the target, such as offering stronger credit schemes. This asymmetry is very evident in Figure 10, where companies with `policy4`, which operate under stricter CO_2 budgets than `policy2` and `policy3`, successfully adapt employee sustainability to meet these tighter constraints.

In summary, introducing CO_2 budgets allows companies to iteratively increase or decrease their CO_2 emissions to match the desired carbon footprint. Dynamically adapting employees' sustainability offers a balanced approach between meeting the desired budget and not overly wasting resources in attempting to decrease the carbon footprint.

D. Real-Time Visualization

To enhance the analysis of our simulation runs, we developed an interactive visualization tool that provides a dynamic, real-time view of the model's behaviour. This tool proved invaluable for identifying critical patterns and anomalies that might have been missed with static outputs alone. So, we can point out several key aspects of the simulation that are displayed simultaneously by our visualization tool, such as:

- **Spatial distribution of transport:** The map interface allows for direct observation of employees steps. This also provides a good perception of how far away the employees live from their companies
- **Temporal changes in transport usage:** Dynamic bar charts track the usage of each transport mode over time. This allowed us to quickly identify trends and shifts in transportation preferences in response to different policies
- **Emissions tracking:** Line graphs illustrate the average CO_2 emissions per company and per employee over time. This feature was crucial for understanding the effectiveness of different policies in reducing emissions and for identifying any unintended consequences
- **Policy impact assessment:** The tool enables a comparative view of emissions and budget adherence across different company policies. This facilitated the identification of the most effective strategies for achieving sustainability goals. Besides that, it also allows for changes in the number of companies (of each policy), the number of workers or even the CO_2 emissions budget cap.

In summary, the real-time visualization tool significantly enhanced our ability to understand the complex dynamics of the simulation model. By providing immediate feedback on the effects of different parameters and policies, the tool facilitated iterative model refinement and supported more informed decision-making.

IV. Conclusions

This study developed a simulation model to examine the impact of modifying transport choices for employees commuting to work. Incorporating real-world commuting data, the model evaluated the system under various scenarios, enabling a comprehensive analysis of potential outcomes. It also facilitated the assessment of how different transport behaviours and company policies influence sustainability, cost efficiency, and carbon emissions. The results of the simulations provided insights into the effectiveness of various interventions in promoting sustainable commuting behaviour.

For **future work**, several enhancements and extensions to the simulation model can be explored. More complex scenarios could be developed by incorporating additional variables such as public transport and traffic congestion. The model could also be expanded to evaluate the effectiveness of specific incentive schemes in influencing transport choices. In addition, future research could focus on developing advanced visualisation tools to enhance the analysis and interpretation of simulation results. Such tools could offer deeper insights into the system's dynamics, aiding stakeholders in making more informed decisions. Finally, the simulation model could be applied to other contexts and regions.

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