Evaluating Impacts of Traffic Regulations in Complex Mobility Systems Using Scenario-Based Simulations

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Abstract

Urban traffic regulation policies are increasingly used to address congestion, emissions, and accessibility in cities, yet their impacts are difficult to assess due to the socio-technical complexity of urban mobility systems. Recent advances in data availability and computational power enable new forms of model-driven, simulation-based decision support for transportation policy design. This paper proposes a novel simulation paradigm for the ex-ante evaluation of both direct impacts (e.g., traffic conditions, modal shift, emissions) and indirect impacts spanning transportation-related effects, social equity, and economic accessibility. The approach integrates a multi-layer urban mobility model combining a physical layer of networks, flows, and emissions with a social layer capturing behavioral responses and adaptation to policy changes. Real-world data are used to instantiate the current "as-is" scenario, while policy alternatives and behavioral assumptions are encoded as model parameters to generate multiple "what-if" scenarios. The framework supports systematic comparison across scenarios by analyzing variations in simulated outcomes induced by policy interventions. The proposed approach is illustrated through a case study aims to assess the impacts of the introduction of broad urban traffic restriction schemes. Results demonstrate the framework's ability to explore alternative regulatory designs and user responses, supporting informed and anticipatory evaluation of urban traffic policies.

Keywords – Urban mobility; traffic regulatios; what-if scenario; modeling complex systems

1 Introduction

The availability of data for sensing and observing urban systems has grown at an unprecedented pace. Advances in pervasive sensing, mobile devices, connected vehicles, and digital platforms now provide access to urban data with increasingly fine-grained spatial, temporal, and social resolution [Zheng, 2019]. In parallel, rapid progress in computational capabilities has substantially expanded. Together, these developments are enabling public authorities and urban decision makers to adopt novel, powerful data-driven paradigms, enabling the systematic evaluation of policy interventions beyond what was previously feasible.

These technological advances have brought renewed attention to one of the central research frontiers in urban studies and transportation science: complexity. Cities cannot be adequately understood as collections of independent subsystems or through purely reductionist models. Rather, they exhibit the defining characteristics of **complex systems-of-systems**, in which multiple interacting subsystems, such as transportation, land use, energy, governance, and social behavior, co-evolve over time. Moreover, urban systems are inherently **socio-technical**, as technical infrastructures and control mechanisms are tightly coupled with human decision-making, social norms, institutional constraints, and adaptive behaviors. These interactions

give rise to non-linear dynamics, feedback loops, path dependencies, and emergent phenomena that challenge traditional modeling and evaluation approaches.

Urban mobility systems constitute a paradigmatic example of such socio-technical complex systems [Batty, 2008, McPhearson et al., 2016, Luca et al., 2024]. Transportation networks are not merely physical infrastructures supporting vehicle flows; they are shaped by—and in turn shape—individual and collective behavior, economic incentives, regulatory frameworks, and social practices. Interventions such as traffic regulations, access restrictions, pricing schemes, or infrastructural changes can trigger individual and social responses and behavioral adaptations that are difficult to anticipate using aggregate or static models alone.

This paper contributes to this line of research by proposing a **model-driven, simulation-based paradigm for decision support in urban mobility policy design**. The objective is to enable the ex-ante evaluation of both direct impacts—such as traffic conditions, congestion, modal split, and emissions—and indirect impacts arising in related domains. These include transportation-related effects (e.g., parking displacement), social impacts (e.g., differential constraints on mobility for vulnerable groups), and economic consequences (e.g., accessibility of city centers, tourism, and local commerce). By supporting systematic exploration of policy alternatives before implementation, the proposed approach aims to reduce uncertainty and unintended consequences in urban traffic regulation.

The approach is inherently **simulation-based**, allowing the representation of the current **"as-is"** state of the mobility system alongside multiple **"what-if" scenarios** corresponding to alternative traffic policies and structural changes in urban mobility. This enables controlled experimentation on policy options that would be impractical, costly, or ethically problematic to test in real-world settings.

At its core, the framework relies on an **urban mobility model** that explicitly integrates a physical layer, including the transportation network, traffic flows, and pollutant emissions, with a social layer capturing individual and collective behavior, adaptation mechanisms, and varying degrees of behavioral rigidity. This coupling is essential to represent the socio-technical nature of urban mobility systems and to account for behavioral responses to policy interventions.

The "as-is" scenario is instantiated using directly measured and estimated quantities derived from available data sources. These include mobility-related indicators such as vehicle volumes, origin–destination matrices, and emissions, represented at both macro and micro levels. Policy alternatives are then defined through model parameters that encode endogenous events (e.g., public authority regulations), exogenous events (e.g., infrastructure disruptions or changes in vehicle fleets), and assumptions on user responses and behavioral adaptation.

Simulation outputs characterize the system behavior under each "what-if" scenario, with particular emphasis on variations in outcomes such as traffic patterns and emissions, induced by changes in model parameters. The framework also supports systematic comparison across scenarios and against the baseline "as-is" condition. We remark that the scope of this work is not causal inference or factor discovery: we assume that relevant factors and their relationships to the modeled phenomena are given and encoded in the model structure, and policy analysis is conducted by manipulating input parameters, generating alternative system states, and comparing their simulated outcomes.

To illustrate the proposed approach, we apply it to a **case study in the city of Bologna**, Italy, a major urban center characterized by a large resident population and a complex, multimodal mobility system. The case study focuses on assessing the direct and indirect impacts of a hypothetical newly introduced traffic fee aimed at regulating vehicular circulation within a designated urban area. Building on the city's existing limited traffic zone in the historical center, we simulate—for experimental purposes—an additional circulation restriction applied to a broader area. This setting enables us to demonstrate the ability of the proposed framework to construct, analyze, and compare multiple "what-if" scenarios, reflecting alternative regulatory designs and heterogeneous user responses, and to support informed evaluation of traffic regulation policies before their implementation.

This paper is structured as follows. Section 2 presents the conceptual framework of the study, highlighting the transportation policies and the standard evaluation methods, as well as explaining the challenges in modeling mobility systems. Section 3 outlines the general architecture of the proposed methodological pipeline and its application to a specific case study. Section 4 formalizes the mathematical model constructed for the case study. Section 5 details the implementation and application of the model, reporting the assessed

results. Finally, Section 6 summarizes the main findings and discusses the limitations and challenges for future research.

2   Conceptual framework

2.1   Policy application and evaluation

In recent decades, transportation policies have assumed a central role in the international political agenda, driven by the need to balance the traffic externalities with economic growth, social equity and accessibility, and environmental objectives. The literature has identified various types of traffic policy interventions, reflecting different strategic approaches to address transport challenges. Operationally, these policies can be categorized according to whether they target the supply side or the demand side of the transport system.

Supply strategies are designed to increase the quality of the supply and, hence, its traffic capacity and efficiency. Examples of such traffic policies are the modifications to the transport infrastructure, both aimed at equipping the system with new facilities (e.g., the construction of a new highway or a new railway connection), and at enhancing the existing system through maintenance and expansion (e.g., the increase of the capacity of an existing road through the introduction of new lanes). Similarly, the technological enhancement of the supply, towards the constitution of Intelligent Transport Systems, is designed to monitor and manage traffic in real-time and provide information to travelers about traffic conditions, enabling better route choices and reducing congestion. Another key example of supply policy is the optimization of the public transport systems, where the scheduling and the routing are recalibrated to properly balance the mobility demand with the mobility offer. As demonstrated by Rhoads and Shogren [2006], supply-side policies tend to have a higher social discount rate and are often preferred to obtain immediate and tangible changes in the transport system. However, they may induce additional demand and generate the so-called induced traffic, sometimes offsetting long-term benefits [Goodwin, 1996, Downs, 2004, Hymel, 2019].

Alongside, demand-side traffic policies address the mitigation of congestion by altering the demand for transportation [Lindsey et al., 2023, Small et al., 2024]. These demand-side approaches take various forms, including access regulations that limit entry and circulation in specific zones or roads, for all vehicles or specific categories. Taxation measures, such as fuel taxes and vehicle ownership taxes, also play a key role in discouraging the use and/or the possession of private vehicles, in favor of other transport modes. Similarly, adjustments to public transport fares can incentivize or disincentivize ridership, while carpooling initiatives may encourage shared vehicle use. Finally, pricing schemes introduce user charges for accessing certain roads or zones, often to limit vehicular traffic congestion.

As widely described by de Palma and Lindsey [2011], the enactment of pricing policies serves to internalize the marginal social cost imposed by travelers, who contribute to collective traffic congestion and its negative externalities, and are therefore required to bear their share of this collective cost. Beyond the original theoretical framework proposed by Pigou [1920] for computing optimal traffic fees, practical implementations of pricing policies exhibit considerable variation. Common approaches include area-based charging (i.e., tolls for entering or passing through designated zones) and facility-based charging (i.e., tolls for using specific roads or lanes). These schemes also differ significantly in their temporal implementation, with some applying flat charges during the whole day and others during peak hours, while more advanced systems employ dynamic, real-time pricing strategies that adapt the pricing fee to current traffic conditions [Bonsall et al., 2007]. Pricing schemes commonly differentiate by vehicle characteristics (e.g., fuel type, registration year, weight) and often include discounts or exemptions for specific vehicle categories and driver groups.

The implementation of these traffic policies raises the critical question of how to evaluate their effectiveness and measure their impact on congestion mitigation. Many studies have focused on assessing the effects of traffic policies on urban factors of interest, from traffic itself to economic growth and social equity, utilizing several analytical tools such as quantitative descriptions, causal inference, and econometrics to evaluate ex-post effects [Foreman, 2016, Zhang et al., 2025, Gibson and Carnovale, 2015, Börjesson and Kristoffersson, 2018]. Ex-post evaluations as such, however, require the policy to be enacted before its assessment is possible, and hence fail in providing policy makers with a formal and quantitative analysis of the short- and

long-term effects of the policy. Instead, ex-ante evaluations address this task and provide evidence on the effectiveness, or not, of a policy proposed.

Cost-Benefit Analysis (CBA) represents the standard tool for policy evaluation, being among the most widely discussed, tested, and used techniques [Koopmans and Mouter, 2020]. In CBA, the societal value of a new policy is evaluated by comparing in monetary terms the total cost related to its implementation (e.g., planning and construction costs) and the benefits that it causes (e.g., savings in fuel consumption, savings in maintenance). While it is effective at assessing direct and tangible effects, CBA is often criticized for its difficulty in fully capturing externalities. Many of these are not easily linked to a clearly defined economic metric, which can result in distorted or biased estimates [Næss, 2020]. Other comprehensive methodologies have emerged in response to the persistent gap between standard policy evaluation practices and the theoretically ideal comprehensive solutions [Oliveira and Pinho, 2010, Koopmans and Mouter, 2020, Næss, 2020]. However, a major challenge remains: once the quantities of interest have been identified, one must propose a model that can capture the system's response mechanisms to policy implementation and adequately adjust these quantities accordingly. Only by adopting such a modeling approach, outcome differences can be estimated rigorously and robustly, thereby allowing for their appropriate evaluation.

2.2 Socio-technical mobility systems: models and challenges

Since their initial development in the 1950s, the goal of mobility models has been to provide a systematic methodology for quantifying the effects of changes in the underlying transportation systems [van Nes and de Jong, 2020]. For example, the four-step model has long been used to structure mobility analysis and to anticipate the economic impact of large-scale infrastructure projects [McNally, 2007]. Similarly, System Dynamics offers an aggregate representation of system behaviour to explore how complex dynamics may unfold over time in strategic long-term policy scenarios [Shepherd, 2014]. Recent methodological advances and new applications have further enabled researchers to address increasingly specific questions and to study diverse transportation contexts. Macroscopic models capture aggregate system behaviour [Wilson, 1970, McNally, 2007, Shepherd, 2014], while microscopic models represent individual agents and their interactions [Rilett, 2001, Horni et al., 2016, Lopez et al., 2018, PTV Group, 2025]. Both are widely used to explore what-if scenarios, such as assessing how mobility patterns may change under alternative policy interventions, as illustrated in the works by Rieser et al. [2008], Brand et al. [2019], Melkonyan et al. [2020], Daniel et al. [2021], Asgarpour et al. [2023].

While models differ in focus and detail, they address and integrate fundamental components to capture the essential elements that allow researchers to describe, understand, and analyze the complex phenomena under study. First, mobility systems are intrinsically socio-technical complex systems [Batty, 2008, McPhearson et al., 2016, Luca et al., 2024]. Social components (e.g., people, organizations, cultures, processes) and techniques (e.g., technologies, infrastructures, tools) are deeply interconnected and influence each other. They integrate physical infrastructures, technologies, and digital systems with individual behaviors and social practices components, and the interactions of these closely connected components give rise to complex, emergent behaviors and trade-offs inherent to large-scale socio-technical systems [Sussman, 2000]. Capturing this complexity is a key challenge and requires comprehensive, fair, and efficient models capable of supporting and improving informed decision-making processes on policy development and scenario analysis.

Uncertainty is another inherent feature of mobility systems, closely related to their complexity, as it measures "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" [Walker et al., 2003]. Cities face a wide range of unpredictable events, from natural disasters and health emergencies to sudden economic shifts or policy changes. Even in stable conditions, human behavior adds another layer of unpredictability: people adjust their habits, react differently to incentives, and sometimes resist new regulations in ways that defy precise modeling [Avineri and Prashker, 2004]. Uncertainty emerges across multiple dimensions. For instance, data limitations may introduce bias and incompleteness, while, at the modeling stage, simplifications and context-dependent assumptions can obscure complex causal relationships. Moreover, in forecasting, small inaccuracies tend to accumulate over time, potentially leading to large deviations between projected and observed outcomes [Mannucci et al., 2023].

Another key challenge is the growing demand for transparency, interpretability, and accountability.

Stakeholders require clear explanations of model assumptions, mechanisms, and limitations to trust the results and use them effectively for decision-making. Similarly, citizens need understandable information about how models influence policies and daily life, so that they can engage with decisions that affect their communities [Luca et al., 2024].

The domains of modeling, analysis, and civic engagement are all shaped by these challenges. Rather than treating them as isolated problems to be eliminated, researchers should acknowledge their interdependence and adopt an integrated, holistic approach. By encompassing this interconnected perspective, modelers can create tools that are both analytically rigorous and socially meaningful, supporting trust, participation, and more informed policy choices.

3   Methodological framework

3.1   Motivating case: traffic regulation pricing policy

The motivating case considered focuses on an urban area characterized by recurring congestion during peak hours and significant levels of atmospheric emissions. In such contexts, implementing traffic regulation policies is crucial, yet their evaluation proves challenging due to the complex interactions between user behavior, network characteristics, and regulatory parameters. The policy under study is a traffic pricing system, where tolls vary according to temporal and categorical criteria, with exemptions for specific user groups and a defined application schedule.

The complexity of the case becomes evident when observing how demand responds to the implemented measures. Users' choices are heterogeneous and influenced by factors such as travel time, availability of alternative transport modes, and individual habits. The overall effect of the policy on traffic and emissions cannot be intuitively determined in a purely intuitive manner, as interactions between individual behaviors and regulatory measures generate nonlinear dynamic phenomena. In addition, uncertainty may be present in the unpredictable strategic response of users to the applied regulation. This clearly demonstrates the need for a systemic approach capable of simultaneously modeling the physical urban layer, user strategies, and policy parameters. Evaluating the effectiveness of interventions requires a framework that can represent both the policy and the behavioral diversity of users, while preserving the dynamic interdependencies within the system.

The main contribution of this framework is to generate comparable "as-is" and "what-if" scenarios, including their behavioural implications. This scenario generation constitutes the analytical starting point for policy appraisal: methods such as cost-benefit analysis depend precisely on such consistent "as-is" and counterfactual configurations, and the framework is designed to supply them in a transparent and reproducible manner. By examining these scenarios, the motivating case provides a concrete illustration of the challenges that the proposed framework aims to address. It clarifies why a systematic approach is necessary to link regulatory interventions, behavioral responses, and resulting system states in a coherent and reproducible manner. The case also lays the conceptual foundation for the framework's components: scenarios representing the initial conditions of the system, policy parameters defining the intervention, and behavioral strategies representing user responses. Through this lens, the motivating case becomes a tangible demonstration of the complexity inherent in urban traffic systems and the rationale for adopting a structured modeling approach.

3.2   General framework architecture

As Figure 1 depicts, the model evaluates the current scenario and, together with a set of external control parameters, simulates the changes that lead to a modified scenario. This allows for the evaluation of the policy impacts by comparing the baseline and the modified configurations.

Within a spatio-temporal domain, a **scenario** is described by its core quantities of interest, which are the measurable variables that the model aims to consider, describe, and evaluate. They refer to the relevant aspects of reality, including physical and environmental features (such as the road network and the land use), social characteristics (such as the number of people with specific attributes), and the dynamics of
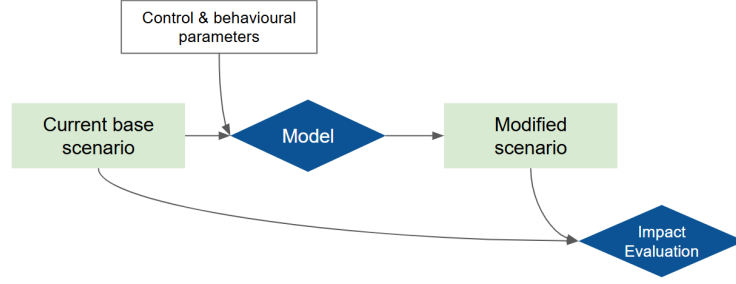
Figure 1: Schematic representation of the architectural framework for what-if scenario analysis

the complex civic system. In the baseline scenario, the quantities of interest are inferred directly from the real-world data within the spatio-temporal domain of the analysis. Indeed, the baseline scenario represents the current conditions of the analysed framework and serves as a benchmark for measuring the impact of any intervention introduced. In contrast, the modified scenario represents the situation after the implementation of changes in the current system, and the values of the quantities of interest are estimated throughout the model.

The changes described above can result from either exogenous or endogenous events. Exogenous events originate from outside the system, such as changes in the environment, new regulations, or unexpected external shocks. Endogenous events, in contrast, emerge from within the system itself, arising from internal interactions or natural changes that develop over time within the system. In both cases, the goal is to model these events using a series of **control parameters**. Their definition is problem-dependent and has the objective of identifying the key characteristics of the event and schematizing them with a certain number of parameters.

When an event alters the current state, changes occur as direct and indirect **consequences of, and reactions to, the event**. Direct effects refer to interventions that impose structural modifications on the system (e.g., closing a road that alters the accessibility of the road network, or constructing new buildings with public services that change land use patterns). Indirect effects include aspects within the transport domain (e.g., the modal shift towards public transport) or strongly correlated (e.g., impacts on logistics), but they also include broader secondary effects, such as impacts on the city economy (e.g., impact on merchants and shopkeepers, impact on city tourism, etc.) and social aspects (e.g., limiting the right to mobility, or imposing disproportionate disadvantages on specific vulnerable groups). The effects are complex to model, as they require identifying the potential behavioral response of people and describing it through explicit formulations.

The model accounts for user responses by identifying and representing plausible **behavioral strategies**. For instance, when new traffic regulations are introduced, users may either maintain their current habits or adjust them, depending on policy relevance, adaptation convenience, or inherent user characteristics. In defining these strategies, it is important to capture the interdependencies between possible behaviors and the features of both the scenario and the policy. Accordingly, strategies are specified conditionally, based on control parameters and additional behavioral factors.

The development of the modified scenario begins from the original system conditions. These conditions are altered through the occurrence of an event, defined by control parameters, which directly modifies the system and indirectly the users' habits in the system. The combined effects extend through the system, affecting the key variables under study. The **impact evaluation** is hence assessed by comparing the baseline initial measures with the new modified ones. The extent of the change is measured as the variation in the quantities of interest.

In this framework, variables can be defined either deterministically, with fixed values, or stochastically, as random variables following probability distributions. The probabilistic formulation allows us to explicitly

represent input **uncertainty** and trace how it propagates through the model to the final estimates of the quantities of interest. By treating parameters probabilistically rather than as fixed values, the model can be evaluated repeatedly, with each run producing potentially different outputs that reflect the underlying uncertainty. An ensemble approach enables the quantification of output uncertainty, either through small variations in input values or, in the case of nondeterministic models, by using different seeds for the random processes.

3.3 Application to the case study

In the motivating case, the primary goal is to assess the effectiveness of a newly introduced traffic fee aimed at regulating vehicular traffic in a specific urban area by limiting vehicle circulation. Given this scope, key variables for analysis include vehicular traffic flow measurements alongside additional metrics on vehicle emissions and air quality, which will act as performance metrics for the restrictions on circulation and on pollution. The policy is defined by control parameters that quantify the regulatory restriction across temporal boundaries, affected user bases, and economic burdens imposed by the measure. Furthermore, the model captures user reactions as a function of both behavioral attributes and the defining properties of the policy. This section presents these variables and the interconnected relationships that allow moving from one to the other, as summarized in Figure 2.

Three core variables are observed and monitored in the baseline and modified scenarios. The **emissions** measure the overall pollutants generated by the vehicles circulating in the area. Moreover, two other quantities control the number of vehicles and thus measure the effects of policy limitations: the **inflow** represents the number of vehicles entering the area affected by the policy regulation, and **traffic** defines the number of vehicles circulating in the area. These indices can be derived from various real-world mobility data sources, including traffic counting sensors that monitor vehicle flows, origin-destination matrices that capture travel patterns between different zones, and GPS or mobile phone data that provide movement trajectories. Their elaboration leads to the characterization of the current baseline scenario.

The policy enacts a area-based traffic regulation for which the vehicular circulation in a designated area is limited. In this example, the regulation imposes a fee on all vehicles circulating into the area during the daily hours. The cost depends on the type of vehicle in circulation: to achieve emission reduction goals alongside traffic reduction, different penalty levels can be applied to vehicles based on their emission standards, for instance, with higher costs assigned to older, more polluting classes. Moreover, the policy provides payment exemptions for vulnerable social groups.

In response to the implementation of the regulatory policy, affected travelers reassess their transportation habits and may modify them accordingly. The model introduces behavioral parameters, designed to define users' attitudes and preferences and account for the most likely **behavior strategies**. Among them, the most plausible, included in the model, are: *rigidity* (i.e., portion of travelers, among the affected ones, that continues with their usual mobility habits), *time-shifting* (i.e., fraction of affected travelers that accepts shifting their trip to an earlier time before the policy becomes active or to a later time after the policy ends), and *mode-shifting* (i.e., portion of travelers that decides to change the mode of transport from private vehicles towards public transport means). If none of the other alternatives are viable, travelers may give up their usual trip and become *lost vehicles*. This case models trip cancellations, for instance, but also changes to other modes of transport not monitored in this model (e.g., foot, bicycle).

The application of the policy and its effects on the user travel behaviours initiate a sequential process that progressively alters inflow, traffic, and emission levels in the **modified scenario**. The effects on the inflow follow directly from the policy implementation. In the new scenario, the inflow varies from the base one with time: it may be reduced when the policy is applied, and there remain only exempted and rigid travelers; on the other hand, it may be increased in the hours of policy inactivation, when anticipating and postponing travelers are to be added to the base inflow. When aggregating traffic from all vehicles, both those starting their journey inside the area and those arriving from outside, the total traffic volume changes in accordance with the variations in the number of vehicles. The new scenario is hence associated with a modified value of total traffic in the area per time instant. This causes changes in the vehicular emissions from the area, which vary according to the traffic. The policy and the subsequent scenario modification
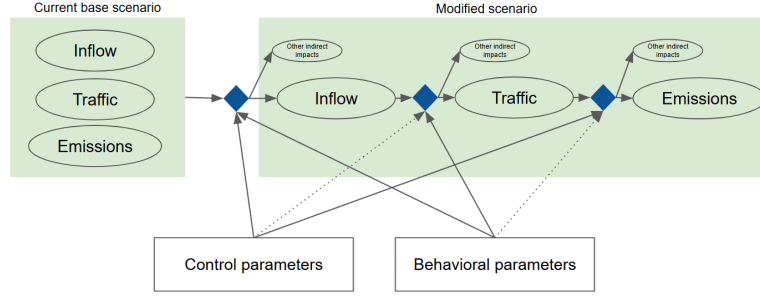
Figure 2: Conceptual diagram of the case study, showing the main quantities of interest (i.e., inflow, traffic, and emissions) in the current and modified scenarios. Blue squares represent modeling steps that map inputs to outputs, allowing for the assessment of the modified quantities

affect other measurable quantities which could be important for a complete policy assessment. For instance, within the transport domain, the extent of the modal shift towards public transport can be assessed.

4 Mathematical formulation

4.1 Scenario definition

The analysis focuses on an urban area, of which a portion of interest is designated for the policy implementation, and other external areas surround it. The analysis considers one reference working day, with measures taken during the 24 hours of the day with a sampling frequency ν. The policy is assumed to be applied on the reference day during designated time slots, with a starting time t_s and an ending time t_e. A fraction of vehicles is exempted from its action, F_e, while it targets non-exempt vehicles with the fee amount varying according to the vehicle emission standard, $\{C_{0l}\}_{l=0,\dots,n_l}$.

Among the quantities of interest, $I(t)$ represents the vector of inflows, that is, the number of vehicles entering the area in each time interval t. In the current base scenario, these inflow values are treated as known parameters, obtained through estimation procedures applied to real traffic data, while in the modified scenario, their values are estimated with the application of the behavioral models explained in Section 4.2. The other two core variables are $T(t)$, representing the number of circulating vehicles in the area during time interval t, and $E(t)$, which denotes the emissions produced by all vehicles circulating within the area during time interval t. The estimation of these quantities is presented in Section 4.3 and Section 4.4, respectively, and follows from the known inflow and starting patterns combined with the emission level distribution of the active vehicle fleet.

4.2 Inflow modifications

The implemented policy, adding a fee for vehicle access to the designated area, is expected to have significant effects on the vehicles circulating in the area. Indeed, the group of travelers directly subject to the fee is very likely to reconsider and adjust their transportation choices. The model simulates different behavioral strategies applied by directly affected travelers in response to the policy application: the maintenance of previous habits (i.e., rigidity), the variation of the travel starting time to avoid the time slot of the policy (i.e., time-shifting), the variation of the mode of transport from private vehicles to another transport means (i.e., mode-shifting), and the cancellation of the travel. These options represent only a subset of the possible responses, chosen as the most relevant for this case study, while acknowledging that other behavioral adaptations may also occur. Moreover, since individuals indirectly affected by the policy, such as those

exempt from it or entering the area outside its activation hours, are expected to maintain largely unchanged behavior, the model formulation concentrates exclusively on the vehicle segment directly influenced by the policy.

The affected travelers select among these strategies reflecting the trade-offs that they make between convenience, cost, and compliance with the policy. In general, the likelihood of each behavioral option is evaluated by looking at the difference between the effort required by the policy and the effort that travelers are willing to accept. "Effort" here refers to the general cost or burden imposed by the policy rather than solely monetary expense. For instance, those considering advancing their departure time will weigh the burden of schedule changes against their willingness to travel earlier; those evaluating modal shift will assess their effort to favour alternative transport over private vehicles; while those contemplating unchanged behavior will compare the monetary cost imposed by the policy against their willingness to pay. The probability of each response is modeled through distinct formulations, since the nature of the decision process varies across the different behavioral options. Then, the optimal behavior is selected either as the single option with minimal effort or as one among several options that each require an acceptably small effort. The following paragraphs discuss behavioral strategies and choice strategies, modeling both the propensity for each behavioral option and the final selection of a strategy.

Probability of rigidity and time-shifting: The formulation of the model for rigidity and time-shift is already present in the literature, and it is known as the Exponentiated Linear Elasticity Model [Hursh et al., 1988, Koffarnus et al., 2022]. Our formulation is a special case of the model, where the slope and coefficient of the demand curve are set to 0.

Let X denote the variable of acceptable effort, that is, the maximum effort that individual travelers are willing to admit. Let us assume that this variable follows an exponential distribution of density $f(x) = \lambda \exp\{-\lambda x\}$. Among the behavioral parameters of the model, it is possible to specify the median of this distribution, $X_{50\%}$, that corresponds to the acceptable effort for 50% of travelers, and that is related to the parameter λ through the formula $\lambda = \ln(2)/X_{50\%}$.

Taking this distribution into account, once the effort required by the access policy X_0 is known, it is possible to compute the probability that the required effort is less than the acceptable effort. This probability also represents the likelihood that such effort will be accepted by travelers, thereby identifying the proportion of travelers ready to adopt the behavioral strategy.

$$\mathbb{P}[\text{accept the strategy}] = \mathbb{P}[X \geq X_0] = \exp\left\{-\frac{\ln(2)}{X_{50\%}} \cdot X_0\right\} \tag{1}$$

Equation 1 is applied to estimate the probability that travelers will maintain their travel routine and demonstrate travel rigidity. In this context, the effort corresponds to the monetary cost of the policy per emission level l, C_{0l}, compared with the maximum acceptable cost, C, exponentially distributed with median $C_{50\%}$. Using Equation 2, it is possible to calculate the probability of accepting rigidity per emission level as $\mathbb{P}[C \geq C_{0l}]$ during the policy application.

$$\mathbb{P}[\text{rigidity for Euro-level } l] = \mathbb{P}[C \geq C_{0l}] = \exp\left\{-\frac{\ln(2)}{C_{50\%}} \cdot C_{0l}\right\} \tag{2}$$

By reweighting the probability with the proportion of vehicles belonging to each emission level class, the probability of overall rigidity acceptance is found, as in Equation 3.

$$\mathbb{P}[\text{rigidity}] = \sum_l P_l \cdot \mathbb{P}[\text{rigidity for Euro-level } l] = \sum_l P_l \cdot \mathbb{P}[C \geq C_{0l}] \tag{3}$$

The postponement of trips is evaluated by assessing the effort of a time variation from the current travel starting time to the policy ending time, $\Delta_{te}(t) = t_e - t \; \forall t \in [t_s, t_e]$. The time variation is to be compared with the maximum acceptable time variation, Δ_p, exponentially distributed with median $\Delta_{p50\%}$. As Δ_{te} depends on the time, the probability of postponement is also time-dependent on each starting time interval t throughout Equation 4.

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$$\mathbb{P}[\text{postponement in time } t] = \mathbb{P}[\Delta_p \geq \Delta_{te}(t)] = \exp\left\{-\frac{\ln(2)}{\Delta_{p50\%}} \cdot \Delta_{te}(t)\right\} \tag{4}$$

Similarly, Equation 5 uses the acceptance anticipation Δ_a, the required anticipation per time interval $\Delta_{fs}(t)$, and the median parameter $\Delta_{a50\%}$, to compute the probability of accepting anticipation. However, to fully avoid the circulation policy, the trip should be anticipated to be completed before the policy start. Consider the travel time in the area, modeled as a random variable with a geometric distribution $\tau \sim \mathcal{G}eom(p = \frac{1}{\tau})$ over the support $\mathbb{N}_{>0}$. Then the probability of anticipation can be found as in Equation 5.

$$\mathbb{P}[\text{anticipation in time } t] = \sum_{T=1}^{\infty} \mathbb{P}[\Delta_a \geq \Delta_{fs}(t) + \tau | \tau = T] \cdot \mathbb{P}[\tau = T] = \varepsilon \cdot \exp\left\{-\frac{\ln(2)}{\Delta_{a50\%}} \cdot \Delta_{fs}(t)\right\} \tag{5}$$

where $\varepsilon = p\,e^{-\ln 2/\Delta_a 50\%}[1 - (1-p)e^{-\ln 2/\Delta_a 50\%}]^{-1}$.

Probability of mode-shifting: The probability of the change in the mode of transportation is modeled through a logit model [Ben-Akiva and Bierlaire, 1999]. It is based on the principle that the probability of changing between two modes of transport depends on the relative effort of the options. In this case, since focusing on the shift from private to public transport, the model incorporates covariates related to the availability of the public transport system, as well as indicators of the overall convenience of making the change, to assess the modal shift proportion. As the public transport distribution is not homogeneous in the city, we characterized subzones of the metropolitan areas with their indicators of availability and convenience, and applied independent modal shift formulations for each travel zone. Consequently, each external origin zone generating trips to the area is assigned a specific probability of modal shift.

Let p_z be the probability of accepting a mode shift to the public transport when starting the trip in zone z. Then, its logit is related to the linear combination of the coefficients β_j and the transport convenience covariates x_{zj}.

$$\ln\frac{p_z}{1 - p_z} = \beta_0 + \beta_1 x_{z1} + \beta_2 x_{z2} + \beta_3 x_{z3} + \beta_4 x_{z4} \tag{6}$$

Two covariates, x_{z1} and x_{z2}, represent the objective characteristics of public transport supply and their adequacy relative to travelers' needs per zone: frequency and capillarity. The frequency is defined as the passage frequency of public transport at stops, and is considered an index of service availability. For each stop and line passing through it, the average number of hourly passages is calculated. By then aggregating this value by zone, the average passage frequency of the vehicles at the stops in the area is obtained. The capillarity is defined as the proportion of the transportation network covered by the public transport system, and is considered a proxy of the service accessibility. It is calculated per zone as the ratio of the transport network length served by public transit routes, determined by matching the network to the public transit routes, to the total transport network length.

Two additional indices, x_{z3} and x_{z4}, evaluate the convenience of public transport compared to private transport: cost and time difference. The cost of the public transportation service is the fare that a user would pay to travel via public transportation from any zone to the area of interest, evaluating the economic convenience of the mode-shift. The difference in travel times when using public transport and when using private means, then, assess the temporal convenience of the mode-shift.

The coefficients $\beta_0, \ldots, \beta_4$ reflect the relative importance assigned to each attribute in the modal choice by travelers. They are not estimated through regression but are treated as behavioral parameters, set in advance.

For each zone of origin, the probability of the modal shift is given by Equation 7.

$$\mathbb{P}[\text{modal shift from zone } z] = \text{logit}^{-1}\{\beta_0 + \beta_1 x_{z1} + \beta_2 x_{z2} + \beta_3 x_{z3} + \beta_4 x_{z4}\} \tag{7}$$

By reweighting the probability with the proportion of vehicles starting in each zone, Z_z, the probability of overall modal shift acceptance is found, as in Equation 8.

$$\mathbb{P}[\text{modal shift}] = \sum_z Z_z \cdot \mathbb{P}[\text{modal shift from zone } z] \tag{8}$$

Optimal strategy choice: After evaluating the available options, travelers decide what to choose, and the model accounts for the different evaluation methods they use. For instance, Travelers may assess options either sequentially, considering them one after the other and giving priority to certain behaviors, or simultaneously, comparing all alternatives to identify the most suitable choice. In this paper, travelers are assumed to consider the options simultaneously and independently of one another, and then decide their strategy as the one that they prefer. This represents a modeling choice; however, the framework can readily accommodate alternative decision-making models, such as the sequential evaluation strategy or hybrid approaches that combine multiple decision rules.

The Equations 3, 5, 4, and 8 report the marginal probabilities that a specific strategy is acceptable for travelers. Since the acceptability of a strategy is independent of the others, the fact that a traveler finds option X acceptable does not influence the probability that they also find strategy Y acceptable. As such, a traveler can find themselves in different situations: they may find acceptable a single strategy, or no strategy, or any combination of strategies, without one excluding the others in terms of acceptability level. In the case of acceptance of multiple strategies, the traveler must nonetheless choose which one to concretely implement. The model assumes that in this situation, the traveler is indifferent among the acceptable options and selects one at random with uniform probability. For example, if k acceptable solutions, each has a probability $1/k$ of being chosen.

Let's take an example with the calculation of the fraction of rigid travelers. This will be equal to the fraction of non-exempt individuals who accept rigidity but do not accept any other strategy, plus the portion of non-exempt individuals who accept both rigidity and another strategy and then randomly choose the former with probability $1/2$. To this, we add the portion of non-exempt individuals with three accepted strategies, including rigidity, who randomly choose rigidity over the other solutions with probability $1/3$. Finally, we include cases where non-exempt individuals find all four strategies acceptable and, among them, choose rigidity with probability $1/4$. Note that, since the marginal probabilities of anticipation and postponement are time-dependent, also the fraction of rigid varies with time $t \in [t_s, t_e]$. In general, given any strategy X chosen from those available, $E = \{\text{rigidity}, \text{anticipation}, \text{postponement}, \text{mode-shift}\}$, the fraction of travelers choosing such a strategy is calculated as in Equation 9.

$$F_X(t) = (1 - F_e) \cdot \sum_{S \subseteq E; X \in S} \frac{1}{|S|} \prod_{Y \in S} \mathbb{P}[Y](t) \prod_{Z \notin S} (1 - \mathbb{P}[Z](t)) \tag{9}$$

Those that do not accept any of the strategies become part of the *lost* vehicles, either canceling the trip, or changing to other transport modes rather than public transport, or choosing other options not accounted for in the model. The fraction of lost vehicles is computed as the fraction of non-exempted vehicles, multiplied by the probability of not accepting any of the behavioral strategies proposed, as in Equation 10.

$$F_{lost}(t) = (1 - F_e) \cdot \Big((1 - \mathbb{P}[\text{rigidity}])(1 - \mathbb{P}[\text{anticipation}](t)) $$
$$(1 - \mathbb{P}[\text{postponement}](t))(1 - \mathbb{P}[\text{modal-shift}]) \Big) \tag{10}$$

Strategies for time-shifting: Having determined the proportion of vehicles adopting each behavioral strategy, most categories can be directly processed: rigid and exempt vehicles contribute to the calculation of the inflow during policy time slots, while mode-shifted and lost vehicles are removed from the analysis. On the other hand, time-shifting vehicles require an additional layer of analysis. Besides deciding whether to shift their departure time, these drivers must also determine how much to anticipate or delay their trips. For instance, a driver who chooses to avoid a policy by departing earlier faces the second decision of how far in advance they should actually travel. This temporal reallocation introduces another modeling phase, as these vehicles must remain in the daily total count while being redistributed across different time intervals according to specific shifting behaviors.

This model accounts a time-shifting strategy that separates the shifting decision into two stages. First, travelers decide whether to accept time-shifting based solely on avoiding the policy period, regardless of the

specific alternative timing. Then, those who accept are redistributed to new departure times before or after the policy period without considering their original departure preferences.

Specifically, from the first phase, the fraction and, therefore, the number of vehicles that choose a time shift are identified. Then, the total of vehicles anticipating TN_a and postponing TN_p are calculated as in Equation 11.

$$
\begin{aligned}
TN_a &= \sum_{t \in [t_s, t_e]} F_{anticipation}(t) \cdot I(t) \\
TN_p &= \sum_{t \in [t_s, t_e]} F_{postponement}(t) \cdot I(t)
\end{aligned}
\tag{11}
$$

Through the second phase, the redistribution of these totals is modeled both before and after the policy's duration. The reasoning applies to both anticipation and postponement, but let us now consider the case of postponement. The random variable Δ_{pr} indicates the time variation that travelers are willing to make when postponing their redistribution, specifically, the time span between their new trip's starting time and the policy's end. The exponential distribution is chosen for Δ_{pr} because it naturally reflects decreasing willingness as time shifts increase (most travelers accept small schedule changes, but fewer accept larger disruptions). It has median $\Delta_{pr50\%}$, scale parameter equal to $\lambda = \frac{\ln(2)}{\Delta_{pr50\%}}$, and the density $f_{pr}(x) = \lambda \exp\{-\lambda x\}$. When determining how many trips will be moved to a specific time interval t, requiring a time shift from the policy end $\Delta_{fe}(t)$, the analysis requires the density of travelers whose personal tolerance exactly matches this required shift. This density directly gives the rate at which trips concentrate at time interval t, computed as in Equation 12. The same reasoning applies symmetrically to anticipations, where we consider the random variable Δ_{ar} with median $\Delta_{ar50\%}$, density f_{ar}, and the time variation is measured until the start of the policy period, denoted as $\Delta_{ts}(t)$.

$$
\begin{aligned}
F_{pr}(t) &= \mathbb{P}[\Delta_{fe}(t-1) \leq \Delta_{pr} \leq \Delta_{fe}(t)] = \exp\left\{-\frac{\ln(2)}{\Delta_{pr50\%}}\Delta_{fe}(t-1)\right\} - \exp\left\{-\frac{\ln(2)}{\Delta_{pr50\%}}\Delta_{fe}(t)\right\} \\
F_{ar}(t) &= \mathbb{P}[\Delta_{ts}(t-1) \leq \Delta_{ar} \leq \Delta_{ts}(t)] = \exp\left\{-\frac{\ln(2)}{\Delta_{ar50\%}}\Delta_{ts}(t-1)\right\} - \exp\left\{-\frac{\ln(2)}{\Delta_{ar50\%}}\Delta_{ts}(t)\right\}
\end{aligned}
\tag{12}
$$

The absolute number of anticipated redistributed vehicles at each time interval is then computed as the fraction $F_{ar}(t)$ multiplied by the total anticipating TN_a. Similarly, the number of postponed redistributed vehicles is assessed multiplying $F_{pr}(t)$ by TN_p.

$$
\begin{aligned}
N_{ar}(t) &= F_{ar}(t) \cdot TN_a \\
N_{pr}(t) &= F_{pr}(t) \cdot TN_p
\end{aligned}
\tag{13}
$$

Inflow in the modified scenario: Given the proportion of vehicles implementing each behavioral strategy, it is possible to calculate the number of vehicles entering the policy-affected area under the modified scenario. Equation 14 presents the formulation for computing the inflow, which distinguishes between two cases depending on policy application time. Within the period of enaction of the policy, with $t \in [t_s, t_e]$, the inflow is the sum of exempted vehicles and rigid vehicles. Outside the hours of the policy, with $t \notin [t_s, t_e]$, the inflow is modified from a portion of vehicles that anticipate and postpone the starting time and sum to the original vehicles.

$$
I_m(t) = \begin{cases} \left(F_e + F_{rigidity}(t)\right) \cdot I(t) & t \in [t_s, t_e] \\ I(t) + N_{ar}(t) + N_{pr}(t) & \text{otherwise} \end{cases}
\tag{14}
$$

4.3 Traffic estimation model

In addition to the entrances, the policy affects the amount of traffic in the area. Our methodology does not attempt to model traffic variations directly; rather, its purpose is to capture the relationships between inputs and traffic, thereby enabling the estimation of modified traffic conditions given modified inflows.

The total traffic load is generated by two sources: trips entering from outside the area (i.e., inflow) and trips starting within the area itself (i.e., starting trips). At any time interval t, one component of the traffic load consists of newly initiated trips, both inflow and starting trips, that begin during that interval. However, traffic does not reset at each time interval but evolves progressively as trips progress through the network. Many trips that are active at time $t-1$ remain active at time t, creating a temporal dependency between consecutive observations. This persistence means that the current traffic state is not independent from the previous one, but rather builds upon it. Consequently, the remaining traffic component is given by a fraction of the previous traffic load that persists into the current time step. Quantifying this persistence through a retention probability allows us to relate the evolution of traffic load to the pattern of trip departures over time.

Given inflow and starting, we model traffic as a discrete-time system with observation intervals of ν-minutes. At time $t=0$, the initial traffic in the observation area is $T(0) = I(0) + S(0)$, where $I(0)$ represents vehicles entering from outside, i.e., the inflow, and $S(0)$ represents vehicles starting their journey within the area. Then, for $t \in \mathbb{N}_{>0}$, traffic evolves according to the following Equation 15:

$$T(t) = I(t) + S(t) + \alpha \cdot T(t-1) \tag{15}$$

where α is the retention probability, representing the fraction of vehicles circulating at time $t-1$ that will remain in the area at time t.

Our approach models the retention probability, α, based on assumptions about the dwell time in the area. Each trip is characterized by the duration for which it remains active within the area, i.e., the dwell time. We assume dwell times follow a geometric distribution with constant mean [Grimmett and Stirzaker, 2001]. This choice is motivated by the memoryless property of the geometric distribution, which corresponds to assuming a constant per-step departure probability, independent of the elapsed dwell time. It also assumes that dwell times are independent of traffic conditions and that probabilities remain stable over time, regardless of congestion levels. Within this discrete-time framework, the retention probability α represents the probability that a trip does not end in a given time step and can be directly related to the mean dwell time.

Specifically, let τ be the trip dwell time following a geometric distribution with mean dwell time $\bar{\tau}$, that is, $\tau \sim \mathcal{G}eom(p = \frac{1}{\bar{\tau}})$ over the support $\mathbb{N}_{>0}$. This yields to the formulation of the retention probability α as a function of the average dwell time $\bar{\tau}$, as $\alpha = \frac{\bar{\tau}-1}{\bar{\tau}}$.

The objective is to compute the traffic vector satisfying Equation 15. Although this system admits a direct solution, we adopt an iterative approach as outlined in Algorithm 1. The direct and iterative approaches are mathematically equivalent and yield identical solutions; however, the iterative formulation empirically assesses superior computational performance, particularly in terms of execution time, and is hence chosen for the implementation . The starting point is an initial guess for the traffic values, $T(t)^0 = I(t) + S(t)$ for all t. Then, at each iteration step k, the algorithm recomputes the value of the retention probability α^k and updates the traffic estimate T^{k+1}, as shown in Equation 16.

$$\begin{cases} T(0)^{k+1} = T^0(0) \\ T(t)^{k+1} = I(t) + S(t) + \alpha^k \cdot T(t-1)^k \quad \forall t > 0 \end{cases} \quad \forall k > 0 \tag{16}$$

The estimation is repeated until the traffic vector T^* satisfies the initial equation 15 given a certain tolerance γ. Specifically, convergence occurs when γ is not overcome by the maximum difference of traffic in subsequent iterations, $\max_t |T^{(k)}(t) - T^{(k-1)}(t)| \leq \gamma$. A maximum number of iterations is also added to ensure a finite execution time.

Having described the traffic model, we now address the computation of its input data, which are required to estimate the traffic vectors in both the reference and policy scenarios. First, in the reference scenario, T is computed using the inflow and starting vectors I and S. The inflows I and the starting trips S are extracted from observed data representing the current situation. Then, in the policy scenario, the modified traffic T_m is estimated starting from the corresponding modified vectors I_m and S_m, where I_m is adjusted according to the procedures outlined in the previous subsection. For the starting vector, the same reasoning applied to the inflow can be adopted. All vehicles that start within the area of interest, excluding exempted

Input:
- Inflow and starting vectors $I, S \in \mathbb{R}_{\geq 0}^n$
- Average reference dwell time $\bar{\tau} \in \mathbb{N}_{>0}$ (expressed in ν-min intervals)
- Convergence threshold $\gamma \in \mathbb{R}_{>0}$
- Maximum iterations $K \in \mathbb{N}_{>0}$

$\alpha^{(k)} \leftarrow \frac{\bar{\tau}^{(k)}-1}{\bar{\tau}^{(k)}}$;   /* Retention probability */
$n \leftarrow \text{length}(I(t))$;   /* Number of time intervals */
$T^{(0)}(t) \leftarrow I(t) + S(t) \quad \forall t \in \{1, \ldots, n\}$;   /* Initialize traffic vector */
$T^{(1)}(t) \leftarrow T^{(0)}(t) \quad \forall t \in \{1, \ldots, n\}$;   /* Copy initial state for iteration */
$k \leftarrow 1$;   /* Iteration counter */
while $k \leq K$ **and** $\max_t |T^{(k)}(t) - T^{(k-1)}(t)| > \gamma$ **do**
    $T^{(k+1)}(t) \leftarrow T^{(0)}(t) + \alpha^{(k)} \cdot T^{(k)}(t-1) \quad \forall t \in \{2, \ldots, n\}$;   /* Update traffic vector */
    $k \leftarrow k + 1$;   /* Increment iteration counter */
end

Output: $T^{(k)}$;   /* Estimated traffic profile */

Algorithm 1: Traffic Estimation Algorithm

vehicles, are required to pay a ticket fee and are therefore directly affected by the policy. As a result, they may decide whether and how to adjust their mobility habits with rigidity, time-shifting, mode-shifting, or cancelation. The modified starting vector was computed following the same procedure used for the inflow case, replacing the inflow vector I with the starting vector S.

4.4 Emission estimation model

For the calculation of emissions in the area, it is assumed that each vehicle in circulation produces a value of average emissions per kilometer depending on its characteristics. This work uses the classification of vehicles in Euro emission standards [Selleri et al., 2021], widely adopted in European environmental and transport studies, to standardize the assessment of vehicle emissions and ensure comparability across different regions and datasets. Vehicles are classified into eight Euro classes, from Euro-0 to Euro-7, based on their characteristics such as vehicle type, fuel type, date of the first registration, and maximum emissions per kilometer. Accordingly, we define $\bar{E}_{l,km}$ as the representative average emissions per kilometer corresponding to the l-th Euro-class, with values obtained from the literature. Moreover, let P_l represent the percentage of vehicles for each of the Euro-class l. This proportion reflects the actual composition of the fleet in the current base scenario, derived from the elaboration of real-world data.

The distribution of vehicles varies before and after the implementation of the policy, as the policy imposes different costs on different Euro-classes, which in turn affects the likelihood of vehicles being rigid. Consequently, during the period of application of the policy, the Euro-level distribution of the fleet must be recalculated considering the adjusted proportions of rigid vehicles, while outside this period it must be based on the original distribution. As a first step, the rigidities for each Euro-class must be calculated. Equation 17 represents the allocation of the total rigidity fraction, F_{rigidity}, among different Euro-levels l. In this way, the formula distributes the total rigidity among the partitions proportionally to both the size of the partition and the likelihood of rigidity within it for each time interval $t \in [t_s, t_e]$.

$$F_{rididity,l}(t) = F_{rigidity}(t) \cdot \frac{\mathbb{P}[\text{rigidity for Euro-level } l]}{\sum_j P_j \cdot \mathbb{P}[\text{rigidity for Euro-level } j]} \tag{17}$$

Then, it is possible to compute the Euro-level distribution under the policy enactment. During the period $[t_s, t_e]$, the new proportion $P_{l,m}(t)$ accounts for two contributions. First, it considers the fraction of exempt vehicles $P_l \cdot F_e$, which represents the part of the Euro-class l that is not subject to the policy and remains unchanged. Second, it consider the fraction of rigid vehicles, $P_l \cdot \frac{F_{rigidity,l}(t)}{F_e + F_{rigidity}(t)}$, which represents the proportional contribution of the rigid share of class l compared to the total of rigid vehicles and exempt vehicles.

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Equation 18 formalizes this reasoning.

$$P_{l,m}(t) = \begin{cases} P_l \cdot \left(F_e + \frac{F_{rigidity,l}(t)}{F_e + F_{rigidity}(t)} \right) & t \in [t_s, t_e] \\ P_l & \text{otherwise} \end{cases} \tag{18}$$

Finally, the average emission value per vehicle in the time interval t is calculated as in Equation 19. The formula is applied for the computation of emissions in both scenarios. In this context, the variable $km\nu$ serves as a conversion factor between distance traveled and the corresponding temporal interval elapsed ν. Specifically, it is assumed that each vehicle, regardless of its Euro-level, travels an average distance of $km\nu$ for each unit of time ν.

$$\bar{E}(t) = \sum_l \left(P_l(t) \cdot km\nu \cdot \bar{E}_{l,km} \right)$$
$$\bar{E}_m(t) = \sum_l \left(P_{l,m}(t) \cdot km\nu \cdot \bar{E}_{l,km} \right) \tag{19}$$

The total emissions produced can be determined by multiplying the number of vehicles $T(t)$ in circulation during each time period t by the average emissions per vehicle, as in Equation 20. The formula is applied for the computation of emissions in both scenarios.

$$E(t) = \bar{E}(t) \cdot T(t)$$
$$E_m(t) = \bar{E}_m(t) \cdot T_m(t) \tag{20}$$

5   Implementation and case study

5.1   Technical development

The implementation of the proposed system required work on two complementary fronts: the backend and the front end. On the backend side, the focus was on ensuring efficient computation and robust model execution, handling large-scale mobility and traffic data, and implementing the algorithms described in the previous sections. On the front end, the objective was to provide an accessible and intuitive interface that could be used by domain experts with varying levels of technical expertise. Together, these two components form an integrated technological system that balances computational rigor and usability, and enables both precise estimation of traffic outcomes and interactive policy experimentation.

The backend is responsible for model development and computation. Most implementation is collected in the Python package `civic-digital-twin`, which can be found in the relative GitHub page [MoST Unit - FBK, 2025]. As previously mentioned, every variable in the model is represented as an index. Independent indices can be assigned either fixed point values or parametric distributions, from which values are sampled during the different iterations. Each index is characterized by a name and, if independent, a value; for dependent indices, the relationships to other variables are defined, specifying both the dependencies and their analytical form. This structure enables the construction of a dependency graph, allowing the sequential computation of dependent variable values at each iteration. The entire computation framework is based on an ensemble modeling approach, in which independent models are evaluated in parallel and their outputs aggregated. This approach has a twofold advantage: it reduces the variance of prediction errors and allows the uncertainty of the results to be quantified, for example, in the form of confidence intervals.

The front end was designed to ensure accessibility and usability for domain experts, including those without technical backgrounds. To this end, we developed an interactive dashboard that allows near real-time simulation of what-if scenarios under varying conditions. Users can directly modify key control parameters, described in Section 3 and 4, including policy fees per vehicle type, exempted vehicles, temporal windows of the policy application, behavioral parameters, and public transport settings. On the same page, simulation results are presented clearly and intuitively (see the next Section 5.3 for a wider discussion on qualitative and quantitative results). Global indicators summarize daily information for both the "as-is" baseline and "what-if" modified scenarios. They refer to indicators such as the total vehicle inflow per day, the maximum traffic
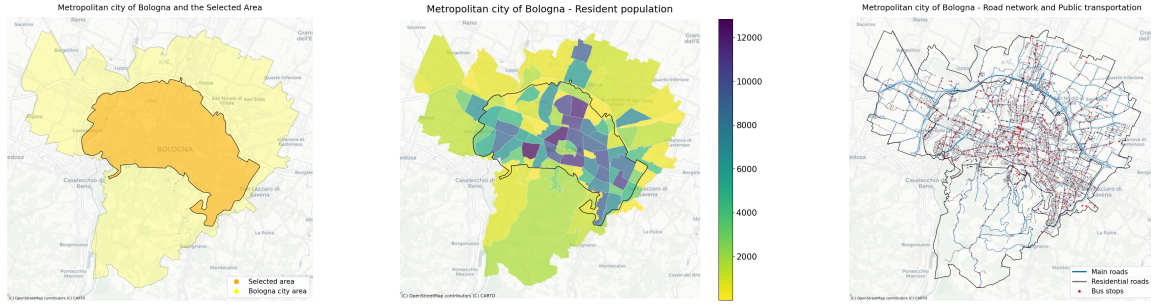
Figure 3: Left: the city of Bologna is highlighted in yellow, while the selected area, subject to the policy, is colored in orange. Center: population distribution in Bologna; the boundary of the selected area is highlighted in black. Right: road network and public transport stops in Bologna; the boundary of the selected area is highlighted in black

within the day, total collected fees, and the estimated emission modification. For insight at a microscopic scale, interactive graphs are included to display the daily evolution of key quantities of interest in the current and modified scenarios. By changing the parameters, users can evaluate multiple scenarios corresponding to different combinations of parameters. The dashboard not only enables comparison between the baseline and modified scenarios, but also across different "what-if" scenarios (e.g., scenario 1 vs. scenario 2), supporting the assessment of alternative policy options.

5.2 Application: the case of Bologna, Italy

The proposed model was tested on a real-world case study in the city of Bologna in Italy, a major urban center with a large resident population and a complex multimodal mobility system. The city is already characterized by a limited traffic zone in the historical center. For experimental purposes, we simulated an additional circulation restriction applied within a broader zone: its northern boundary is delineated by the ring road and the A1-A14 motorway, while the southern boundary follows the city's morphological constraints, namely the hilly area. Figure 3 represents the selected area. This configuration serves as an illustrative example of how the model can be applied to large-scale area-based policies.

The selected area exhibits both strong centrality and high urban attractiveness. It includes more than $321,172$ residents, 82% of Bologna's $392,044$ urban population[1] and 31% of the $1,051,536$ residents in the wider metropolitan province[2]. It concentrates substantial private motorized mobility flows, with $269,226$ daily trips entering the area from outside and $329,807$ internal trips[3]. The road network of the selected area covers approximately 708 km of drivable roads, of which 287 km correspond to primary corridors (i.e., with tags trunk, primary, secondary, and tertiary roads according to OpenStreetMap)[4]. Public transport is also widely available in the area. In particular, for weekdays, the bus routes cover 249 km of the drivable road network with 177 bus lines, operating on a total of 786 bus stops with a median frequency of 14 trips per line per day (range: 1 to more than 100)[5]. The area also includes Bologna Centrale, a major national and regional railway hub. The station serves high-speed and intercity trains to major Italian cities (e.g., Florence,

---

[1]Data extracted from the "Resident Population by Age, Sex, Citizenship, Neighborhood, and Statistical Area" dataset from the Comune di Bologna Open Data portal, version updated 31/12/2024; accessed 12/12/2025. URL: https://opendata.comune.bologna.it

[2]Data extracted from the "Resident Population" ISTAT dataset; accessed on 12/12/2025. URL: https://demo.istat.it

[3]Origin-Destination data are extracted and relaborated from PUMS 2019, provided by Comune di Bologna

[4]Road network data extracted from OpenStreetMap; accessed 8/06/2025. URL: https://www.openstreetmap.org

[5]Bus service data extracted from the Open Data portal of Trasporto Passeggeri Emilia-Romagna (TPER); accessed on 25/05/2025. URL: https://solweb.tper.it/web/tools/open-data/open-data.aspx

Milan, Venice, Rome) as well as international connections, including routes to Munich, and regional and suburban lines connecting surrounding towns and the Modena-Bologna-Ferrara corridor.

Bologna was further selected due to the advanced mobility data infrastructure maintained by the municipality. High-resolution data are collected from multiple sources, including traffic sensors, cameras, and vehicle registration data from the national motorization authority. These datasets are already used for real-time traffic monitoring, allowing us to estimate the current "as-is" traffic situation. In particular, the integration of multi-source data with statistical and data science preprocessing techniques enabled the estimation of inflows into the restricted area as well as trips originating within it, with a temporal discretization of $\nu = 5$ minutes. Furthermore, we have estimates of the daily percentage of vehicles by Euro emission class currently circulating in the area. From Euro-0 to Euro-6 vehicles, respectively, the proportions are 0.059, 0.012, 0.034, 0.054, 0.198, 0.176, and 0.467. Similarly, knowing the vehicular fleet composition in terms of segment, fuel type, and technology, we estimate the pollutant emissions per kilometer per vehicle typology in the area. We focus on the nitrogen oxides (NOx), a group of highly reactive gases emitted by vehicles that significantly contribute to air pollution. For each Euro-level class, the estimated emissions in grams per kilometer are: 0.2105847, 0.217457, 0.2401457, 0.247239, 0.135555, 0.099559, and 0.068246.

5.3   Result assessment

In this section, we present the outcomes of the simulation scenarios under different access pricing policies and behavioural settings. To explore the potential effects of alternative parameter configurations, we construct a set of scenarios and systematically compare their impacts. The purpose of this analysis is not primarily to evaluate specific policies, but rather to illustrate a methodological approach for measuring variations in the model outputs under different conditions with the proposed methodology. The focus is on demonstrating how scenario-based simulations can be used to quantify and analyze changes in key performance indicators.

The comparison between scenarios is assessed by qualitative and quantitative analysis. First, we concentrate on a set of global metrics that summarize overall system behavior. They include the total number of vehicles entering in the area per day (i.e., daily inflow), the maximum number of vehicles circulating in the area during the day (i.e., max daily traffic), and the maximum number of vehicles circulating in the area during the policy activation hours (i.e., max traffic in policy hours). Note that these quantities differ in the measurement units: while inflows measure the cumulative number of entering vehicles during the whole day, the maximum traffic accounts for the maximum number of vehicles circulating at the same time in the interest period. Moreover, the analysis considers the total grams of NOx emitted by the vehicles circulating in the area during the day (i.e., daily emissions). Other than these key mobility indicators, other metrics are reported to better describe the what-if scenarios, such as the absolute number of vehicles changing their habits with a time-shift, with a modal-shift, or in another way (i.e., lost). Finally, the total earnings collected with the access tickets are summarized in the global indicator of daily revenue.

In addition to aggregated values, we present the temporal evolution of these metrics in graphical representations. The visualizations enable us to observe how system dynamics evolve and identify patterns that may not be evident from aggregate values alone. In the following sections, we present time series plots representing inflow, traffic, and emissions within the area of interest throughout the day. The x-axis represents time, while the y-axis displays the indicator of interest. Different colors denote the various scenarios under comparison, enabling a clear visual distinction between policy implementations.

In addition to the baseline scenario, we consider a set of alternative scenarios designed to illustrate the effects of different pricing configurations and target populations. For example, we examine a daily fixed-price policy applied to the entire population during a 10h period (A1), in a longer 12h period (A2), and limited to morning hours (A3) and afternoon hours (A4). Moreover, we consider variations in which the price is differentiated by vehicle emission class with a focus on emissions reduction (A5) or differentiated per socio-economic level of the population to explore the effects of partial exemptions (A6). The parameters defining these scenarios are reported in Table 1. Furthermore, to assess the sensitivity of system outcomes to behavioral assumptions, we compare scenarios in which the same daily fixed-price policy is applied to 100% of the population while adjusting key behavioral parameters to capture extreme cases. These include a highly-reduced cost acceptability (B1), the removal of time-adjustment flexibility (B2), and the removal

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ID	Description	t_s	t_e	F_e [%]	C_0 [€]
A1	Basic policy	8:00 AM	6:00 PM	0	$\{5\ \forall l\}$
A2	Extended-time policy	7:00 AM	7:00 PM	0	$\{5\ \forall l\}$
A3	Emission policy	8:00 AM	6:00 PM	0	$\{10$ if $l = 0, 1, 2, 3; 5$ otherwise$\}$
A4	Exempted policy	8:00 AM	6:00 PM	10	$\{5\ \forall l\}$
A5	Afternoon policy	1:00 PM	6:00 PM	0	$\{5\ \forall l\}$
A5	Morning policy	8:00 AM	1:00 PM	0	$\{5\ \forall l\}$

Table 1: Parameter configuration of the scenarios B1–B4, assessing changes in policy impacts given changes in behavioral parameters. The remaining model parameters are set equal for all the scenarios: among behavioral parameters, $C_{50\%} = 4 - 7$€, $\Delta_{ar50\%} = \Delta_{pr50\%} = 1$ hours, $\Delta_{ar50\%} = \Delta_{pr50\%} = 0.5$ hours, $\beta_0 = -1.24$, $\beta_1 = 4.5$, $\beta_2 = -1.45$, $\beta_3 = -0.30$, $\beta_4 = -0.034$; for the dwell time distribution, $\bar{\tau} = 20$ minutes; for the emission conversion factor, $km\nu = 2.5$

ID	Description	$C_{50\%}$ [€]	$\Delta_{a50\%}[h]$	$\Delta_{p50\%}[h]$	Shift to PT
B1	No economic-flexibility	0.1–0.5	1	1	True
B2	No time-flexibility	4–7	0	0	True
B3	No mode-flexibility	4–7	1	1	False

Table 2: Parameter configuration of the scenarios B1–B3, assessing changes in policy impacts given changes in behavioral parameters. The remaining model parameters are set equal for all the scenarios: among control parameters, $t_s = 8$:00 AM, $t_e = 6$:00 PM, $C_0 = 5$€, $F_e = 0\%$; among other behavioral parameters, $\Delta_{ar50\%} = 1.5$ hours, $\Delta_{pr50\%} = 1.5$ hours, $\beta_0 = -1.24$, $\beta_1 = 4.5$, $\beta_2 = -1.45$, $\beta_3 = -0.30$, $\beta_4 = -0.034$; for the dwell time distribution, $\bar{\tau} = 20$ minutes; for the emission conversion factor, $km\nu = 2.5$

of modal shifts (B3). The parameters defining these scenarios are reported in Table 2.

For the proposed scenarios A1–A6, Table 3 collects the measured value of these indicators. As expected, the results demonstrate that when access policies are activated, there is a significant reduction in inbound flows, traffic, and emissions. It is particularly interesting to assess how the intensity of these reductions varies depending on the applied policy. Scenarios A1–A4 highlight how the policy duration significantly affects traffic and emissions. Scenario A4 results in a larger reduction in daily inflow with respect to A1 (-56.5k vs -44.6k) and in traffic during policy hours (-5.0k vs -1.5k), with a more pronounced decrease in emissions (-209.8k NOx vs -166.7k NOx), but also a substantial reduction in maximum traffic during the day (-1.5k) in contrast to the increase in the A1 scenario (+1.4k). Scenarios A3 and A4 illustrate the effect of timing: the morning policy in A3 produces smaller impacts on inflow (-17.0k) and traffic (-0.6k policy-hours), whereas the afternoon policy in A4 modifies daily maximum traffic moderately (+0.9k) and maximum traffic in policy hours significantly (-4.4k), with emissions (-10.1% vs -11.9%) and revenue (112k in both scenarios) effects more balanced. Regarding policies tailored for Euro-class vehicles or including exemptions, daily inflow reductions range from -51.5k in A5 to -38.4k in A6, with A1 in between (-44.6k), while variations in traffic during policy hours are minor (-1.5k for A5, -1.4k for A6, -1.5k for A1). Emissions reductions follow the same pattern, from -192.8k NOx in A5 to -143.7k NOx in A6. Time- and mode-shifted vehicles, as well as lost vehicles, also show consistent trends across the three scenarios. Overall, the results indicate that despite slight numerical differences, the three scenarios produce broadly comparable impacts on system performance and revenue.

Focusing on the changes in the behavioural assumptions, the global indicators relative to scenarios B1–B3 are reported in Table 4. All scenarios see a reduction in daily inflows and NOx emissions, but the impact on peak traffic and user behavior differs significantly. Scenario B1 shows the largest reductions in inflows (-43%) and emissions (-44%), but peak traffic slightly increases due to time-shifting, suggesting that overall demand

Indicator	Scenario					
	A1	A2	A3	A4	A5	A6
Daily inflow [veh]	-44.6k	-56.5k	-17.0k	-19.6k	-51.5k	-38.4k
	(-26.5%)	(-33.6%)	(-10.1%)	(-11.6%)	(-30.7%)	(-22.9%)
Max traffic in the day [veh]	1.4k	-1.5k	1.2k	0.9k	1.7k	1.1k
	(9.9%)	(-10.7%)	(8.3%)	(6.5%)	(11.9%)	(7.6%)
Max traffic in the policy hours [veh]	-1.5k	-5.0k	-0.6k	-4.4k	-1.5k	-1.4k
	(-10.2%)	(-35.3%)	(-4.7%)	(-31.1%)	(-10.2%)	(-9.8%)
Daily emissions [kg NOx]	-166.7k	-209.8k	-62.7k	-73.8k	-192.8k	-143.7k
	(-26.8%)	(-33.8%)	(-10.1%)	(-11.9%)	(-31.0%)	(-23.1%)
Time-shifted [veh]	46.2k	43.6k	37.4k	42.2k	51.2k	40.4k
Mode-shifted [veh]	86.5k	106.9k	36.5k	41.3k	95.0k	75.7k
Lost [veh]	59.0k	75.4k	18.5k	22.2k	73.3k	49.6k
Daily revenue [€]	230k	293k	112k	112k	255k	217k

Table 3: Comparison of global indicators in the modified scenarios of Table 1 with respect to the baseline situation

Indicator	Scenario		
	B1	B2	B3
Daily inflow variation [veh]	-72.9k (-43%)	-53.7k (-32%)	-24.5k (-15%)
Max traffic variation in the day [veh]	5.2k (0.36%)	-1.1k (-0.08%)	3.9k (0.28%)
Max traffic variation in policy hours [veh]	291 (2.0%)	-2.7k (-19%)	529 (3.7%)
Daily emissions variation [kg NOx]	-273.3k (-44%)	-199.9k (-32%)	-91.9k (-15%)
Time-shifted [veh]	103.9k	2.8k	84.7k
Mode-shifted [veh]	115.3k	95.9k	0
Lost [veh]	121.8k	81.1k	77.2k
Daily revenue [€]	>500	252.5k	271.8k

Table 4: Comparison of global indicators in the modified scenarios of Table 2 with respect to the baseline situation

reduction is not sufficient to prevent congestion during critical hours. The very low revenues (>€700/day) indicate minimal financial uptake, despite substantial adjustments by a subset of users. Scenario B2 achieves a moderate decrease in inflows (-32%) and emissions (-32%), with a clear reduction in peak traffic (-19% in policy hours). This indicates that rigidity and mode-shift alone can effectively mitigate congestion while maintaining significant revenue (€252.5k/day). Finally, scenario B3 shows limited environmental gains (-15% in emissions) and increased peak traffic, reflecting the concentration of demand in fewer hours. Revenues are highest (€271.8k/day), but congestion and lost trips remain substantial.

The qualitative analysis throughout visualizations is shown in Figures 4, 5, and 6. The higher daily maximum traffic in A1 compared to A4 is driven by the combined effect of vehicles anticipating or postponing trips, adding to an already high congestion level, whereas traffic remains more moderate throughout A4. Similarly, A1, A3, and A4 all experience peaks due to anticipatory and delayed trips, generating local surges in flow. Notably, morning traffic is lower overall, which explains why A3 shows smaller total reductions in daily inflow compared to A4. These patterns highlight how both the timing and duration of the policy shape daily traffic dynamics, congestion peaks, and the environmental effectiveness, beyond their impact on total demand. Figure 5 highlights the differences between scenarios A1, A5, and A6, which are present but largely homogeneous over time rather than exhibiting strong temporal patterns. This indicates that, in this case, global indicators are sufficient to capture and analyze the impacts of the scenarios, without requiring detailed time-resolved examination.

Figure 6 illustrates the distribution of the quantities over time for the scenarios B1–B3. The results reveal how behavioral constraints fundamentally reshape traffic patterns under mobility pricing. In scenario
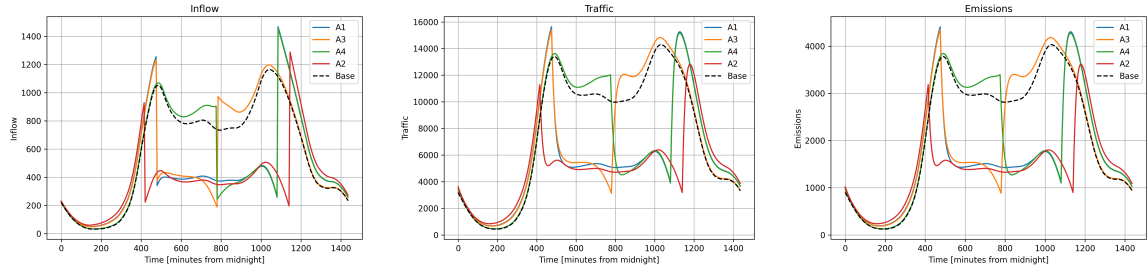
Figure 4: Inflow [veh], traffic [veh], and emissions [g NOx] varying over time for the scenarios A1–A4 of Table 3
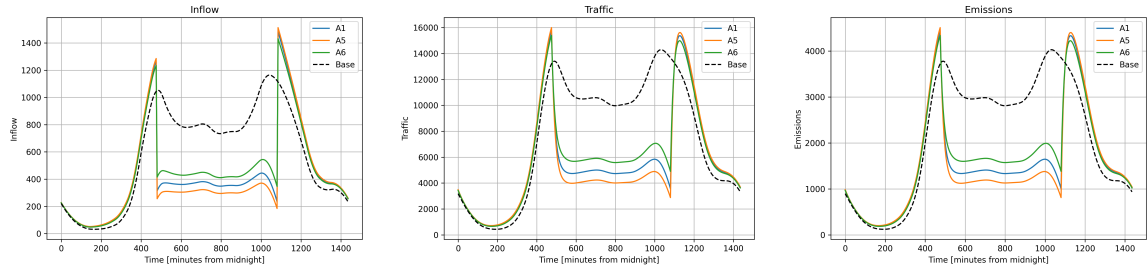

Figure 5: Inflow [veh], traffic [veh], and emissions [g NOx] varying over time for the scenarios A1, A5 and A6 of Table 3

B1, traffic, inflow, and emissions become highly volatile with extreme peaks as travelers concentrate trips to avoid fees, followed by near-zero periods. Scenario B2, on the other hand, produces the most stable outcomes, with sustained moderate flows and emissions, and no high peaks near policy hours. The inability to shift from car to bus (scenario B3) generates an intermediate pattern with significant peaks close to policy activation hours, but maintained baseline traffic within policy hours. The examination of these scenarios highlights the strong dependence of system-level outcomes on behavioral flexibility assumptions, supporting the importance of comprehensive sensitivity analysis. In particular, small changes in travelers' ability to reschedule trips or switch modes can lead to qualitatively different temporal traffic profiles and emission dynamics. These findings underscore that policy evaluations based on a single behavioral specification may be misleading and that robust mobility policy assessment requires explicit consideration of heterogeneous traveler responses.

6 Conclusions

In this study, we presented a model-driven, simulation-based approach for the ex-ante evaluation of urban traffic regulation policies, capable of capturing both direct impacts, such as traffic conditions, modal shifts, and emissions, and indirect impacts, including social and economic effects related to mobility. The application of the framework to the real-world case study of Bologna demonstrated that the integration of a physical layer, representing the transportation system and traffic flows, with a social layer, capturing individual behaviors and adaptation to policy interventions, enables systematic exploration of "what-if" scenarios and assessment of the potential consequences of alternative regulatory designs prior to their actual implementation. The proposed approach addresses the complexity inherent in socio-technical urban mobility systems, accounting for nonlinear interactions, uncertainty, and dynamic adaptation of user behavior, while supporting transparent and reproducible generation of counterfactual scenarios. In this way, it enables rig-
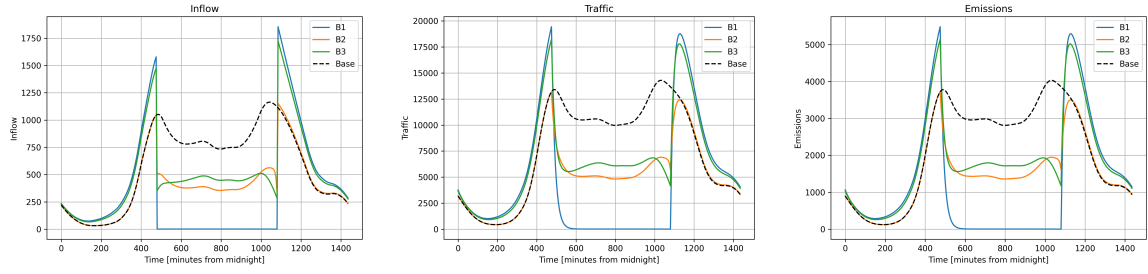
Figure 6: Inflow [veh], traffic [veh], and emissions [g NOx] varying over time for the scenarios B1–B3 of Table 4

orous assessment of traffic policies before their implementation, offering decision makers actionable insights into potential impacts. The evaluation results show that the proposed framework is able to support the analysis and assessment of the impacts of different possible policies and behavioral parameters. In addition, experimenting with extreme scenarios, in particular for what concerns behaviorsal parameters, appears to be a powerful approach to assess the sensitivity to these parameters: this sensitivity analysis is particularly relevant for the evaluation of the potential impacts of mobility policies, given the difficulty to provide precise and accurate models for behavioral parameters.

Several directions could enhance the proposed framework: spatial disaggregation and multi-scale analysis; dynamic behavioral modeling and long-term adaptation; and integration of social equity dimensions. From a spatial perspective, the current model works at a single-zone level and provides aggregated insights for one urban area. A natural extension would involve a multi-scale approach that divides the selected area into finer spatial units. This would enable the evaluation of the same key indicators at a sub-zone level. Such granularity would reveal localized hotspots and spatial patterns that may be hidden by aggregation. This would support more targeted interventions and allow policymakers to design zone-specific measures.

From a temporal perspective, the current model assumes a short-term perspective with independence in individual choices. Extending the temporal horizon would allow policymakers to observe how the urban mobility system evolves over time in response to policy interventions. This would provide insights into the long-term effects of mobility plans and support more informed strategic planning.

Concerning the social dimension, the proposed framework currently focuses on efficiency metrics such as inflows, traffic congestion, and emissions. However, urban mobility policies have different impacts across socio-economic groups. Future work should incorporate indicators of social vulnerability and equity to assess how policy interventions affect disadvantaged communities. By combining efficiency with equity considerations, the model would provide a more complete evaluation framework aligned with principles of environmental fairness and inclusive urban planning.

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