Adaptive and Mixed Incentive Strategies for Spatial Balancing in Bike-Sharing Systems

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***Abstract*—Maintaining spatial balance and ensuring high service availability are persistent challenges in the management of large-scale bike-sharing systems (BSS). This study introduces a discrete-event simulation framework designed to assess the effectiveness of alternative incentive strategies in addressing these issues. The framework simulates a controlled urban setting characterized by heterogeneous user behavior, stochastic demand patterns, and autonomous, station-level decision-making. Three incentive scenarios are evaluated: a no-incentive baseline, a *static* strategy employing fixed rewards, and a *dynamic* approach where stations adapt incentives based on real-time conditions and budgetary constraints. Comparative analysis across key operational and economic indicators reveals that while *static* incentives improve availability, they lead to inefficient resource allocation and elevated costs. In contrast, the *dynamic* strategy achieves more balanced performance by enhancing user engagement and system responsiveness while significantly reducing expenditure. These results underscore the potential of decentralized, adaptive incentive mechanisms to promote scalable, cost-effective, and sustainable management of bike-sharing networks.**

***Index Terms*—Bike-Sharing Systems, Incentive Strategies, Urban Mobility, Adaptive Algorithms, Simulation**

I. Introduction

The rapid expansion of bike-sharing systems (BSS) in urban environments has positioned them as critical components of sustainable and multimodal transportation networks by offering low-emission alternatives to conventional transportation and advancing goals such as traffic congestion mitigation and public health promotion. However, as these systems scale, they increasingly encounter the challenge of spatial imbalance, where bicycles are unevenly distributed across stations due to *dynamic* and asymmetrical user travel patterns. This imbalance undermines service availability and often necessitates resource-intensive rebalancing efforts. In response, recent research and operational initiatives have explored incentive-based mechanisms that encourage users to voluntarily redirect trips to underutilized

stations. These decentralized, user-centered strategies present a promising solution for enhancing efficiency, scalability, and responsiveness of BSS deployments.

Nevertheless, designing effective and economically viable incentive strategies remains a complex problem, particularly in large-scale and heterogeneous urban contexts. The interplay between localized demand variability, user heterogeneity, station-level decision-making, and budget constraints introduces significant uncertainty, making it difficult to predict system-wide outcomes under different strategic configurations.

This study introduces a discrete-event simulation framework developed to systematically evaluate the performance of three incentive strategies under controlled conditions: (i) a no-incentive baseline, (ii) a *static* strategy that applies fixed incentives when bike availability falls below a predefined threshold, and (iii) a *dynamic* strategy wherein stations adaptively adjust incentive levels based on real-time availability, budget status, and strategic behavior modes. The simulation environment models an urban grid with a realistic spatial layout, stochastic demand patterns, and heterogeneous user types, enabling detailed performance evaluation across multiple operational metrics.

By tracking key indicators, such as bike availability, spatial imbalance, trip activity, and financial outcomes, the study provides a comparative analysis of each strategy's operational efficiency and economic viability. The results offer insights into the design and deployment of adaptive incentive schemes capable of enhancing the robustness, sustainability, and user responsiveness of BSS.

II. Related work

The spatial imbalances brought on by asymmetric trip patterns between stations were the focus of early BSS optimization studies. O'Mahony and Shmoys [1] integrated demand data with optimization routines in their study of the CitiBike system in New York City to enhance rebalancing operations, presenting temporally-aware techniques in controlling supply restrictions. Similarly, Zhang et al. [2] investigated how built environment factors, such as population density and proximity to transit, affect demand at the station level. Their results confirm the requirement for geographically contextualized redistribution strategies and highlight the spatial heterogeneity of BSS usage. Fricker and Gast [3] demonstrated that user-based incentives can lower stockout frequency without requiring redistribution vehicles or operational personnel by presenting a model for homogeneous BSS with finite-capacity stations.

Many people are choosing incentive-based solutions over *static* or centrally planned rebalancing. Singla et al. [4] proposed a real-time incentive system that pays users for rerouting their journeys to underutilized stations. Their research demonstrated that system-wide availability can be significantly increased when users respond to even small incentives. Although they concentrated on *static* rebalancing, Chemla et al. [5] offered fundamental insights into the logistics limitations and cost structures related to redistribution, providing a standard by which incentive-based approaches may be measured. Game-theoretic concepts provide a convincing framework for simulating competition and cooperation among system nodes from the standpoint of decentralized control and adaptive strategies. A closed queuing network model, in which each node (such as a station) controls its service policy in response to local conditions, was investigated by George and Xia [6] for fleet sizing in rental systems. Bimpikis et al. [7] applied game theory to spatial pricing in ride-sharing networks to demonstrate how agents can arrive at equilibrium strategies in *dynamic* competition and limited information. These concepts are directly relevant to BSS's adaptive incentive schemes, allowing each

station to modify its reward policy in response to its own and nearby stations' performance. Machine learning and artificial intelligence have recently been used for BSS predictive management. The Diffusion Convolutional Recurrent Neural Network (DCRNN), created by Li et al. [8], combines temporal sequence modeling and spatial graph convolution to estimate traffic patterns, including bike demand, accurately. Their model improves short-term prediction by capturing temporal lags in demand and non-linear correlations between stations. On the other hand, Gammelli et al. [9] suggested a variational Poisson recurrent neural network for predicting demand for bike sharing and assessed its usefulness for inventory management. Their findings showed how predictive models, like station stocking and incentive distribution, may improve forecast accuracy and guide operational decisions.

Additionally, creating efficient bike-sharing regulations still requires an understanding of user behavior. By synthesizing usage data and behavioral studies across global networks, Fishman et al. [10] could identify major user segments and their motives, including proximity, cost, and convenience. Early user responses in North American networks were further investigated by Shaheen et al. [11], who found trends in the willingness to reroute depending on station availability, incentives, and service familiarity. These findings encourage unique incentive strategies catered to user profiles and validate the modeling of user heterogeneity in simulation experiments.

While prior studies have significantly advanced the understanding of demand forecasting, user segmentation, and incentive-based interventions in BSS, many existing approaches are constrained by centralized architectures, *static* incentive rules, or assumptions of user homogeneity. These limitations reduce their applicability in *dynamic*, real-world settings characterized by diverse user behaviors and fluctuating demand. This study addresses these gaps by proposing a decentralized, discrete-event simulation framework in which stations autonomously adjust incentive offerings in real time, guided by localized information. The model integrates heterogeneous user profiles and *dynamic*ally modulates incentive levels based on real-time demand forecasts, shortage risk, available budget, and strategy-specific parameters. By capturing the complex interactions between station-level decision-making and user responses under budgetary constraints, the framework provides a more operationally viable and behaviorally realistic approach. This represents a novel contribution to the field, offering a scalable, context-sensitive methodology for spatial rebalancing that improves economic efficiency, system resilience, and user alignment in BSS networks.

III. Methodology

We developed a discrete-event simulator written in Python, that simulates user behavior, station-level decision-making, and system dynamics across time to assess adaptive incentive methods in BSS. The simulator allows flexible experimentation with user categories, demand distributions, incentive schemes, and spatial layouts.

A. System Architecture and Initialization

The simulation environment is built on a 2D grid-based representation of an urban area. A distinct generator script allows for the fast creation of population and station distribution scenarios by specifying the area grid size, the total population, the number of population clusters in the grid, and the total number of BSS stations. The generator distibutes population in each grid cell following a Gaussian distribution around randomly assigned population cluster centres and then distributes stations probabilistically within each grid cell, according to the population density. At the same time, it calculates a random percentage of each cell's population (within a

defined range) that are registered BSS users. The population and station data are stored as JSON files containing metadata such as coordinates, population density, and popularity scores.

The simulator can then be initialised based on this JSON data, as well as a range of other parameters that are also stored as an external JSON file, including the BSS station docking capacity, pricing parameters, user behavioural category parameters and incentivisation strategy parameters. A number of bikes is randomly allocated to each station initially, in a pre-determined range up to each station's capacity minus two (to allow for docking opportunities).

B. Demand Modeling and Trip Generation

Demand for each station is generated stochastically at each hour of the simulation, based on the population of each grid cell and the proportion of residents who are active users of the bike-sharing system. Specifically, the demand for each station is computed using a formula that combines local population density, a user participation rate (i.e., percentage of residents who are system users), and a temporal demand profile, for which we use a dual-peak Gaussian curve to model morning and evening peaks. Each station has its own demand curve with peaks selected randomly between a paramerizable range (e.g. 7-11am and 4-8pm).

Several user trips are generated per station per hour according to its demand curve. Each trip includes a randomly selected destination, calculated distance, and base price. If no bikes are available at the origin or the destination is completely full, the trip may be canceled or redirected to a nearby station, depending on the station status, incentives offered, user type, and strategy.

C. User Behavior and Typologies

Users are assigned to one of three behavioral categories, consistent with behavioral diversity in real-world BSS:

- **Loyal users:** low likelihood (e.g., 0–10%) of accepting incentives; they prefer convenience over redirection.
- **Flexible users:** moderate likelihood (30–60%) of accepting a redirection incentive.
- **Opportunistic users:** high likelihood (60–100%) of accepting incentives if the offer is attractive.

D. Incentive Logic and Redirection Mechanism

When a destination station is near full or unavailable, the incentivisation system may offer a redirection incentive to a nearby station with more availability. Incentives are computed based on:

- Distance to the suggested alternate station,
- Remaining budget of the station offering the incentive,
- Baseline allowable incentive per trip (defined globally),
- Bike availability at candidate stations and forseen shortage risk.

Users evaluate the offer for attractiveness by applying a distance-based penalty on the presented incentive amount, and have a probability to accept it according to their category thresholds and redirection distance constraints (e.g. 3 grid cells). Successful redirection is aimed to improve system balance.

E. Station Strategies and Adaptive Learning

Stations can be initialized with any of the following incentivization strategies to adopt permanently throughout the simulation (*static* mode), all of which apply a different incentive scaling factor f_i to the calculation of the incentive presented to users. In the simulation *dynamic* mode however, they can dynamically switch between any of the strategies.

- **Conservative:** offers a balanced incentive and preserves the budget ($f_i = 0.5$).

- **Aggressive:** offers high incentives to maximize attractiveness ($f_i = 1.2$).
- **Adaptive:** offers a variable incentive depending on the time of day, based on demand peaks ($f_i \in [0.0, 1.0]$).

dynamic mode examines the station's success rate in incentivising users to select it as a destination, as well as that of nearby stations within the user's maximum redirection range. It also considers the proportion of trips aborted with this station as an origin due to bike shortages and its current spend on incentives. If the station is experiencing many shortages, it reverts to an aggressive strategy. If it is paying out more than neighbouring stations but with a lower success rate, it reverts to being conservative. Otherwise it adopts an adaptive strategy. The adaptive strategy evaluates a station's performance (regarding redirection success, revenue, and budget utilization) against nearby stations.

F. Metrics and Evaluation

Throughout the simulation, the following metrics are recorded:

- Average number of bikes on station per hour
- Average imbalance on station per hour,
- Completed trips per hour,
- Total incentives expenditure per hour,
- Redirected trips per hour,
- Net profit.

IV. Experimental Results

A. Study setup

To investigate the effectiveness of various incentive strategies in addressing spatial imbalances within bike-sharing systems, we designed a comparative simulation study comprising three distinct experimental scenarios. These scenarios progressively incorporate different levels of incentive-driven behavior and strategic diversity across stations. To ensure comparability, all scenarios are executed under identical urban grid and demand conditions.

The first scenario is a baseline, with the incentive mechanism fully disabled. Stations do not offer incentives to influence user behavior; redirection occurs only when the originally selected destination station is full. This setup provides a benchmark for quantifying the value added by incentive-based strategies.

In the second scenario, all stations employ a fixed incentive structure proportional to the cost of the trip ($< 20\%$ of the cost), but only when a station is low on bikes ($< 20\%$ of capacity).

The third scenario introduces strategic heterogeneity by allowing stations to alternate between three strategies: adaptive, conservative, and aggressive. Further from the rules in each strategy, the final incentive offered to the user is contingent on a shortage risk factor $R_{(s,h)}$, a budget factor $\beta_{(s,h)}$ and the incentive scaling factor f_i of the strategy. The risk factor $D_{(h,s)}$ for a station s at hour h is based on the predicted demand for the current hour:

$$D_{(h,s)} = \begin{cases} 2 & h < 24 \\ B_{(s,h)} - D'_{(s,h)} & h > 24 \end{cases}$$

where $B_{(s,h)}$ is the number of bikes currently docked at the station. To calculate the predicted demand $D'_{(s,h)}$, we consider the recorded station's demand history for a time window of n hours ($n = 72$). Therefore the risk factor becomes:

$$R_{(s,h)} = min(1, max(0, -B_{(s,h)}/max(1, D'_{(s,h)})))$$

The budget factor moderates incentives based on the remaining station budget $F_{(s,h)}$ and its initial budget $F_{(s,0)}$:

$$\beta_{(s,h)} = min(1, F_{(s,h)} \times 24/F_{(s,0)})$$

Initial budgets are determined per station proportionally to a maximum value $F_0 = 100$ and the population served by the station. The station serving the grid cell with the largest population receives a daily budget of F_0 and all others receive a daily budget according to the proportion of their grid cell population against that maximum. Thus the final incentive $I_{(s,h)}$ becomes:

$$I_{(s,h)} = I_b \times R_{(s,h)} \times \beta_{(s,h)} \times f_i$$

This setup facilitates examining interactions among diverse station behaviors and explores whether such heterogeneity enhances overall system performance or leads to emergent dynamics.

We ran a simulation for five virtual days in each scenario, with performance data collected hourly, on a 20×20 city grid, with a population of 250k inhabitants and 100 bike stations with a capacity of 10 bikes each (Fig. 1). Key evaluation metrics include trip completion rates, redirection frequency, incentive spending, system balance, and user acceptance of redirection offers. Comparative analysis of the scenarios provides insights into the trade-offs and potential benefits associated with deploying adaptive and heterogeneous incentive strategies in large-scale BSS environments.

B. Study results

This section presents the empirical findings from a controlled simulation study designed to assess the effectiveness of three incentive mechanisms in addressing spatial imbalances in bike-sharing systems. The experimental setup includes a no-incentive baseline, a *static* strategy applying fixed incentives under predefined thresholds, and a *dynamic* strategy that adapts incentive levels based on local demand forecasts, budget constraints, and behavioral modes. The analysis isolates the

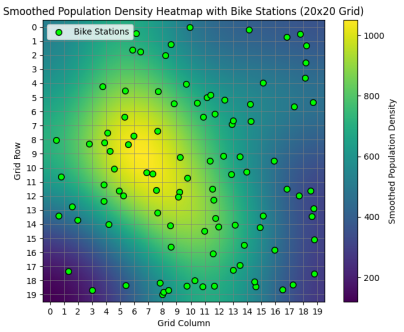


Fig. 1. Simulation urban environment

impact of each strategy on key operational metrics. The performance indicators evaluated include average bike availability, spatial imbalance, completed and redirected trips, incentive spending, and revenue generation. The comparative results provide insight into how different incentive models influence system efficiency, user behavior, and overall sustainability in urban mobility contexts. Where statistical tests are reported, we use the appropriate parametric or non-parametric version according to how data meets relevant assumptions.

The average number of bikes per station per hour is the first metric used to evaluate each incentive scenario's ability to sustain network-wide availability. Figure 2 traces this value over the five-day simulation for three configurations: no incentives, *static* incentives, and *dynamic* strategy allocation. A Friedman test shows that the hourly mean bike availability per station differs with statistical significance across strategies ($\chi^2_{(2)} = 135.74, p < 0.001$). Pairwise Wilcoxon tests with post-hoc Bonferroni correction show that this difference is statistically significant between the strategies *none* and *dynamic* ($Z = -9.178, p < 0.001$), *none* and *static* ($Z = -9.037, p < 0.001$), but not between *dynamic* and *static* ($Z = -1.475, p = 0.14$). In the no-incentive scenario, the series displays pronounced volatility, frequently dipping below 5.5 bikes per station during

demand peaks. Lacking any redirection mechanism, the system is more susceptible to shortages whenever usage increases. Under the incentivization strategies, the mean availability is generally higher. We can notice several instances where the system is able to sustain a better availability where the non-incentivization scheme would exhibit significant dips, holding average availability near 6.0 bikes per station (*Dynamic*: $\bar{x} = 6.06, \sigma = 0.259$; *Static*: $\bar{x} = 6.043, \sigma = 0.243$; *None*: $\bar{x} = 5.707, \sigma = 0.272$).

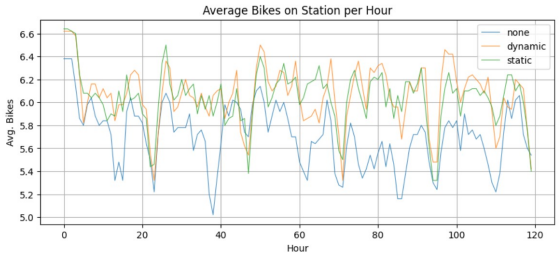


Fig. 2. Average number of bikes per station over time for three incentive scenarios

Figure 3 depicts the hourly evolution of spatial imbalance, defined as the mean standard deviation in bike availability across stations, under the *none*, *static*, and *dynamic* incentive scenarios. A Friedman test shows that the hourly mean imbalance per station does not differ with statistical significance across strategies ($\chi^2_{(2)} = 3.467, p = 0.177$). This means that the incentivization strategies do not lead to an artificially equitable distribution of bikes by redirecting trips to station where the bikes would not be again used. The baseline configuration without incentives shows pronounced volatility and recurrent imbalance spikes during peak-demand periods, revealing the system's limited capacity for self-correction when stations saturate or empty. The *static* strategy achieves a more uniform and generally lower imbalance, indicating that fixed incentives alleviate severe asymmetries, though in a somewhat inflexible fashion. The *dynamic* strategy matches the *static* configuration in overall magnitude yet exhibits smoother transitions and slightly reduced imbalance at critical hours, suggesting that its adaptive logic offers incremental gains in sustaining an even distribution of bikes throughout the network.

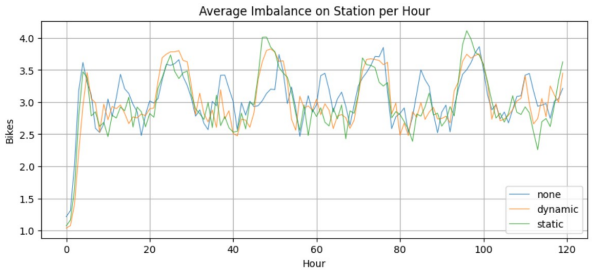


Fig. 3. Average imbalance on station per hour for three incentive scenarios

The distribution of completed trips per hour across the three incentive strategies reveals important differences in overall system performance (Figure 4). The *none* scenario, serving as the baseline, exhibits a lower median and a narrower concentration of values, indicating less consistent trip throughput and a higher likelihood of unmet demand. In contrast, both the *static* and *dynamic* configurations demonstrate higher medians and broader upper ranges, reflecting more frequent achievement of near-maximum trip volumes. Notably, the *dynamic* strategy achieves the most favorable distribution, with a denser clustering of values near the upper end of the range, suggesting that adaptive incentive mechanisms more effectively support sustained system utilization. These findings highlight the advantage of incentive-based interventions, particularly *dynamic* strategies, in maximizing network throughput under varying demand conditions.

A quantitative assessment of total incentive expenditure across the *static* and *dynamic* experimental scenarios reveals pronounced differences in both cost-efficiency

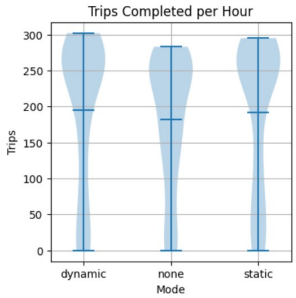


Fig. 4. Completed trips per hour for three incentive scenarios

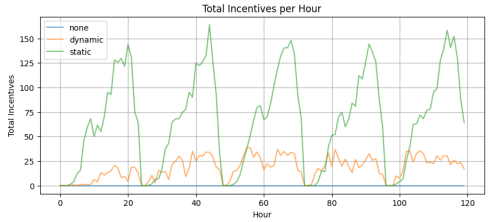


Fig. 5. Total incentives per hour for three incentive scenarios

and deployment methodology. The *static* strategy incurs the highest cumulative expenditure, exhibiting substantial variability and frequent surges exceeding 150 units per hour, particularly during periods of pronounced demand imbalance ($\bar{x} = 66.572, \sigma = 49.189$). Such behavior reflects a deterministic, threshold-based policy that lacks adaptive responsiveness, thereby increasing the likelihood of suboptimal and inefficient resource allocation. Conversely, the *dynamic* strategy sustains a comparatively stable and moderate expenditure profile, typically ranging between 15 and 35 units per hour, enabled by a context-aware decision framework that integrates real-time station-level conditions, budgetary constraints, and strategy-specific incentive modulation ($\bar{x} = 18.164, \sigma = 11.708$). The difference is statistically significant (Wilcoxon test, $Z = -8.233, p < 0.001$). The *dynamic* configuration achieves comparable system outcomes at markedly reduced cost, underscoring its superior operational efficiency within budget-constrained environments (Figure 5).

The temporal distribution of redirected trips provides insight into the responsiveness of each strategy in managing spatial imbalances across the network (Figure 6). As expected, the *none* scenario registers no redirections, as it lacks any incentive mechanism to influence user behavior. The *static* strategy exhibits the highest redirection volume, with frequent peaks surpassing 40 trips per hour ($\bar{x} = 23.583, \sigma = 13.86$). This indicates an aggressive but inflexible application of redirection incentives, which may lead to overuse regardless of necessity. In contrast, the *dynamic* strategy produces a more moderated and stable redirection profile, generally remaining below 20 trips per hour ($\bar{x} = 9.392, \sigma = 5.817$). The difference is statistically significant (Wilcoxon test, $Z = -8.708, p < 0.001$). The adaptive nature of the *dynamic* strategy allows redirections to be deployed more selectively, guided by localized station conditions and real-time demand indicators. While both incentive-driven strategies facilitate corrective user routing, the *dynamic* approach achieves this with lower intervention frequency, suggesting greater efficiency and a reduced burden on user compliance.

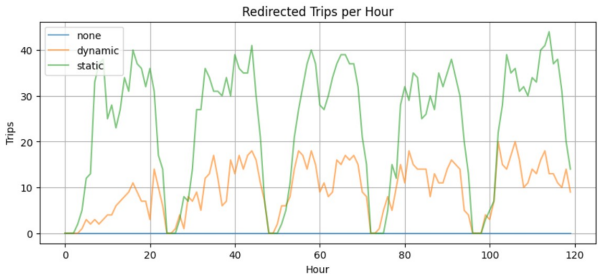


Fig. 6. Redirected trips per hour for three incentive scenarios

The evaluation of total daily revenue across the three incentive strategies reveals marked disparities in economic performance (Figure 7). The first scenario yielded the lowest and most volatile revenue, indicating limited capacity to respond effectively to user demand. Although

the *static* strategy generated higher overall revenue, primarily due to increased trip activity, it also exhibited greater variability and incurred elevated operational costs as a result of frequent incentive deployment. In contrast, the *dynamic* strategy consistently achieved the highest and most stable revenue outcomes. Its real-time, demand-driven incentive adjustments enabled a more efficient balance between user engagement and expenditure control, resulting in improved financial predictability and operational efficiency. Notably, when accounting for incentive-related costs, the net profit associated with the *static* strategy fell below that of the no-incentive baseline. This finding highlights the clear advantage of the *dynamic* approach, which not only enhances financial sustainability but also improves system balance and resource availability through more targeted and context-aware user incentives.

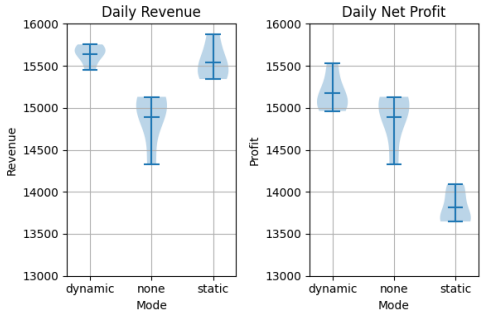


Fig. 7. Average daily revenue and net profit for each strategy.

V. Conclusions

This study presented a simulation-based assessment of incentive strategies designed to address spatial imbalances in BSS. Using a discrete-event simulation framework, we modeled realistic urban demand dynamics, user heterogeneity, and decentralized station-level decision-making to compare three strategic configurations: a no-incentive baseline, a *static* incentive model with fixed thresholds, and a *dynamic*, context-aware strategy responsive to real-time conditions and budget constraints.

The comparative analysis demonstrated that both incentive-based strategies outperformed the baseline in key operational metrics, including bike availability, trip completion rates, and spatial balance. These results validate the effectiveness of economic incentives in shaping user behavior and improving resource distribution. However, the *static* strategy incurred higher costs due to its inflexible deployment logic, often activating incentives unnecessarily and reducing overall cost-efficiency.

By contrast, the *dynamic* strategy achieves comparable or improved outcomes relative to the *static* model, yet with considerably reduced spending on incentives. Its adaptive nature allowed for precise, need-based interventions that improved financial outcomes and system efficiency. These findings highlight the promise of decentralized, adaptive incentive mechanisms as a scalable and sustainable approach to managing BSS networks.

VI. Software and Data Availability

The simulator source code in Python and all data used in this paper is released openly on GitHub, at: https://github.com/komis1/BikeSharingSim.

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