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A Dynamic Operational Framework Integrating Life Cycle Assessment and Ride-Level Emission Modelling for Shared E-Scooter Systems

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Abstract

Shared e-scooter systems are frequently characterized as zero-emission mobility solutions; however, lifecycle greenhouse gas (GHG) emissions depend on manufacturing, electricity generation, and operational logistics. While conventional life cycle assessment (LCA) studies quantify environmental impacts using static average parameters, they rarely integrate lifecycle emissions into real-time fleet decision-making. This study proposes a formally defined carbon-aware operational framework that integrates ride-level telemetry, time-varying electricity grid carbon intensity, amortized production emissions, and dynamically allocated logistics impacts into a unified optimization architecture. Lifecycle emissions are computed at ride-level granularity and incorporated into charging and rebalancing decisions through a constrained optimization framework. A multi-objective extension is introduced to account for environmental–economic trade-offs. An illustrative simulation of 1000 rides was conducted to evaluate the operational performance of the framework. Under the assumed baseline scenario, the illustrative carbon-aware simulation indicated a potential reduction of up to 24.5% relative to conventional scheduling. Sensitivity analysis across variations in grid carbon intensity, scooter lifetime, energy consumption, and logistics emissions demonstrated reduction outcomes ranging between 18% and 29%, indicating robustness to parameter uncertainty. The study does not present large-scale empirical validation but provides a mathematically formalized decision-support architecture that operationalizes lifecycle assessment within shared micro-mobility fleet management. The results suggest that integrating carbon metrics into operational control may substantially enhance the environmental performance of shared e-scooter systems. Future research should validate the framework using real-world fleet data and incorporate a comprehensive economic assessment. The proposed framework provides a scalable methodological basis for integrating environmental metrics into real-time micro-mobility management and urban sustainability planning.

Keywords: shared e-scooters; life cycle assessment; ride-level emission modelling; carbon-aware operations; dynamic operational optimization

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1. Introduction

Urban transportation accounts for a substantial share of global greenhouse gas (GHG) emissions and remains a critical sector for climate mitigation policies [1]. Increasing urbanization and mobility demand intensify environmental pressures in metropolitan

regions. In response, cities worldwide promote electrification, modal shifts, and shared mobility systems as strategies to decarbonize urban transport.

Shared micro-mobility services—particularly dockless electric scooters (e-scooters)—have rapidly expanded in urban environments due to their operational flexibility and zero tailpipe emissions [2,3]. Because of their relatively low operational energy consumption compared to passenger vehicles, shared e-scooters are frequently presented as environmentally sustainable substitutes for short car trips [2]. However, life cycle assessment (LCA) research challenges this simplified narrative. Empirical studies demonstrate that the environmental impacts of shared e-scooters extend far beyond electricity consumption during riding. Manufacturing processes, aluminum-intensive components, lithium-ion battery production, short vehicle lifetimes, maintenance operations, and fossil-fuel-based fleet rebalancing can collectively dominate total life cycle emissions [2–5]. In several deployment contexts, collection and redistribution logistics account for a significant portion of overall climate impacts [2,4]. Moreover, uncertainty in vehicle lifetime assumptions substantially affects amortized manufacturing emissions per kilometer [6]. These findings reveal a central paradox: although shared e-scooters generate zero tailpipe emissions, their overall environmental performance is highly sensitive to operational and lifecycle parameters. Environmental benefits cannot be assumed a priori; rather, they must be systematically quantified and operationally managed. Beyond environmental considerations, shared e-scooters present both advantages and limitations within urban mobility systems. Advantages include flexible first–last mile connectivity, reduced travel time for short trips, and low infrastructure requirements. However, previous research has also identified challenges, such as improper parking, pedestrian space conflicts, safety concerns, and uncertainty regarding actual modal substitution patterns. Stakeholder-based analyses emphasize that environmental, social, and operational dimensions must be evaluated jointly to assess overall sustainability performance [7].

Most existing LCA studies of shared e-scooters rely on static modeling approaches, reporting average emission factors per vehicle-kilometer traveled under fixed assumptions [8,9]. While these approaches are appropriate for comparative environmental assessments, they abstract away temporal variability and operational dynamics. Charging schedules are typically modeled using average grid emission factors, while logistics emissions are estimated using simplified allocation rules. Such simplifications limit the applicability of conventional LCA methodologies for supporting real-time operational decisions in shared micro-mobility systems. To address temporal dynamics in environmental modeling, dynamic life cycle assessment (DLCA) methodologies have been developed. Levasseur et al. introduced time-dependent characterization in LCA [10], and Beloin-Saint-Pierre et al. proposed methodological approaches for dynamic life cycle assessment that incorporate temporal differentiation of lifecycle inventories, enabling time-dependent emission allocation within LCA frameworks [11]. Subsequent applications demonstrated the relevance of dynamic approaches in energy and infrastructure systems [12]. Despite these advances, DLCA methodologies have rarely been applied to shared micro-mobility operations.

In parallel, research on marginal emission factors has shown that electricity-related carbon intensity varies significantly over time [13]. Carbon-aware scheduling strategies aligning energy consumption with low-carbon electricity periods have achieved measurable emission reductions in energy-intensive systems [14]. Similar carbon-aware charging approaches have been explored for electric vehicle fleets [15]. However, these approaches typically operate at aggregate system levels and do not integrate lifecycle-based emission allocation with ride-level telemetry in shared e-scooter systems. At the operational planning level, recent research has investigated the spatial deployment and service-area optimization of shared e-scooter systems using GIS-based multi-criteria decision-making methods [15]. While these studies contribute to sustainable deployment strategies, they generally do not

incorporate dynamic lifecycle emission modeling into daily operational control. Taken together, the literature reveals three interrelated gaps:

1. Static LCA studies quantify lifecycle impacts but lack temporal and operational resolution.
2. Dynamic LCA methodologies incorporate temporal sensitivity but remain largely disconnected from shared micro-mobility practice.
3. Carbon-aware operational strategies exist in energy and fleet contexts, but rarely integrate lifecycle impact allocation at ride-level granularity.

This study addresses these gaps by proposing a carbon-aware operational framework that integrates ride-level telemetry, time-varying electricity grid carbon intensity, and dynamically allocated lifecycle impacts into a unified decision-support architecture for shared e-scooter systems. Rather than treating sustainability assessment as a retrospective reporting exercise, the proposed approach reframes it as an operational decision-making problem. By embedding ride-level carbon metrics into charging, rebalancing, and fleet management processes, the framework enables carbon intensity to function as an operational control variable. Therefore, this work advances lifecycle assessment from static environmental accounting toward actionable, real-time environmental management in shared micro-mobility systems. The remainder of this paper is structured as follows. Section 2 presents the methodological framework and system architecture. Section 3 describes the simulation design and sensitivity analysis. Section 4 discusses operational implications, broader sustainability considerations, and methodological limitations. Finally, Section 5 concludes the study and outlines directions for future research.

2. Methodology and System Architecture

The proposed system is a multi-layered, carbon-aware operational framework for shared e-scooter fleets (Figure 1). Its objective is to estimate greenhouse gas (GHG) emissions at the ride level and integrate these estimates into operational decision-making processes. Unlike conventional static LCA approaches [8,9], which rely on average emission factors detached from operational variability, the framework incorporates temporally varying grid carbon intensity [13] and ride-level operational telemetry.

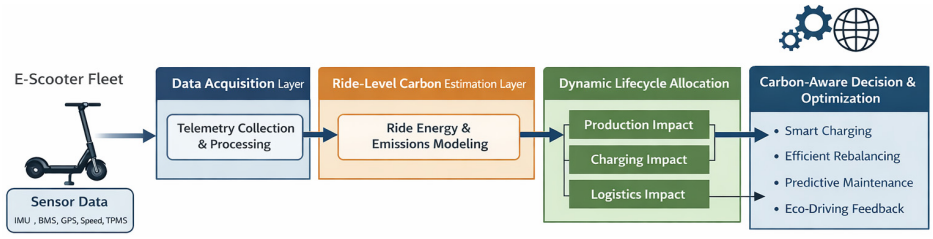

Figure 1. Overview of the proposed carbon-aware system architecture for shared e-scooter operations.

The framework follows a layered design in which ride-level telemetry data collected from the scooter fleet are first processed to estimate energy consumption and associated operational emissions. These ride-specific estimates are then combined with dynamically allocated lifecycle impacts—including production, charging, and logistics-related emissions—to generate ride-level carbon intensity metrics. Finally, the resulting carbon information is integrated into an operational decision and optimization layer, enabling carbon-aware charging, rebalancing, predictive maintenance, and eco-driving interventions. This layered structure reflects a conceptual integration of three research streams:

(i) lifecycle assessment of shared micro-mobility systems [2–6,16],
(ii) dynamic LCA methodologies [10–12], and
(iii) carbon-aware operational control in energy and mobility systems [14,15].

2.1. Telemetry Acquisition and Ride Segmentation

Operational data are collected from on-board sensors, including the following:

- Inertial Measurement Unit (IMU)
- Battery Management System (BMS)
- Global Navigation Satellite System (GNSS)
- Wheel encoders
- Optional Tire Pressure Monitoring System (TPMS)

Telemetry streams are synchronized and segmented into discrete ride *r* events, forming the fundamental unit of analysis. This ride-level segmentation addresses a limitation identified in recent systematic reviews of micro-mobility LCAs, where fleet-level averages obscure intra-day variability and user behavior heterogeneity [16].

2.2. Ride-Level Energy Consumption Estimation

Ride-level electrical energy consumption is estimated using battery voltage and current measurements obtained from the BMS. Total energy consumption for a ride *r* is calculated as follows:

$$E_r = \int_{t_0}^{t_1} V(t)I(t)dt \quad (1)$$

where *V(t)* represents battery voltage, *I(t)* represents current, and t_0–t_1 denote ride start and end times. Unlike static LCA studies that assume average energy intensity per kilometer [2,4], this formulation captures user-specific riding behavior, route characteristics, and temporal variability.

2.3. Lifecycle Emission Allocation

2.3.1. Production and End-of-Life Impacts

Manufacturing and end-of-life emissions are treated as fixed lifecycle quantities amortized over expected service lifetime distance, consistent with micro-mobility LCA practice [2,4,6]. Let C_{prod} denote total production emissions and L the expected lifetime distance. The amortized emission factor is as follows:

$$c_{prod} = \frac{C_{prod}}{L} \quad (2)$$

The production-related emission allocated to ride r with distance d_r is:

$$C_{prod,r} = c_{prod} \cdot d_r \quad (3)$$

Lifetime uncertainty is explicitly acknowledged, consistent with sensitivity analyses in mobility LCAs [6]. Recent multi-city analyses further demonstrate that lifetime assumptions significantly influence total system emissions [17].

2.3.2. Charging Emissions with Temporal Resolution

Charging emissions are modeled dynamically using the time-varying marginal grid carbon intensity γ(t), reflecting hourly electricity emission factors [13]. Charging emissions associated with ride r are computed as follows:

$$C_{charge,r} = \frac{E_r}{\eta_{ch}} \cdot \gamma(t_{charge}) \quad (4)$$

where t_{charge} denotes the time at which the consumed energy is replenished. To partially capture charging losses, charging efficiency is represented by η_{ch}. Power limit and detailed SOC–time dynamics are not fully modeled in the illustrative simulation and are

acknowledged as future extensions. This formulation enables identical rides to produce different carbon footprints depending on charging time and grid conditions. Such temporal sensitivity aligns with dynamic LCA principles [10,11] and carbon-aware scheduling frameworks [14]. Empirical evidence from multi-city LCA studies confirms that variability in the electricity mix can significantly alter total e-scooter emissions [17]. In the illustrative simulation presented, $\gamma(t)$ is treated as an hourly marginal grid carbon-intensity proxy intended to represent diurnal variation in electricity-related emissions. The profile is synthetic and is not mapped to a specific electricity market; therefore, it should be interpreted as a structurally representative signal rather than an empirical regional dataset.

2.3.3. Logistics and Rebalancing Emissions

Fleet rebalancing emissions are allocated proportionally to rides based on spatial demand imbalance and redistribution effort, following shared mobility LCA methodologies [2,4,5].

While deployment optimization models improve service efficiency and station allocation [18,19], they typically do not allocate redistribution emissions dynamically at the ride level. The present framework extends prior work by incorporating rebalancing-related emissions into per-ride carbon intensity metrics.

2.4. Ride-Level Carbon Intensity Computation

Total ride-level carbon intensity is computed as follows:

$$C_{total,r} = C_{prod,r} + C_{charge,r} + C_{logistics,r} \quad (5)$$

This additive formulation reflects standard LCA system boundary principles [8] while introducing ride-level granularity.

2.5. Carbon-Aware Operational Decision Layer

Ride-level carbon estimates are embedded into operational decision-making processes. As illustrated in Figure 2, the decision logic includes the following:

- Carbon-aware charging (delay charging when grid intensity is high)
- Combined or optimized rebalancing strategies
- Predictive maintenance interventions
- Eco-driving feedback mechanisms

The framework remains algorithm-agnostic and compatible with heuristic, rule-based, or machine-learning-based optimization approaches [15].

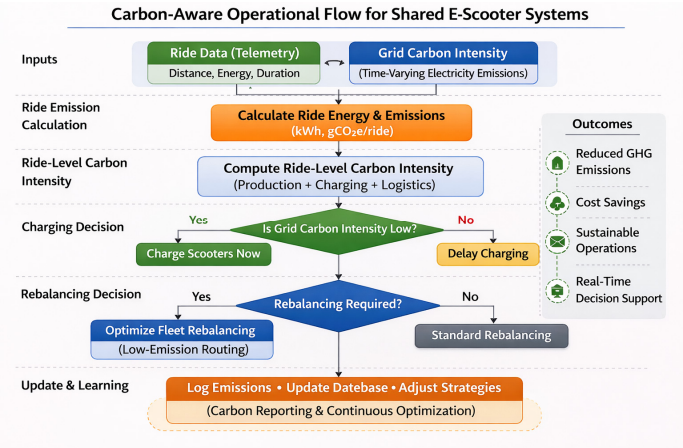

Figure 2. Carbon-Aware Operational Flow.

By treating carbon intensity as an operational control variable rather than a post hoc reporting metric, the framework operationalizes sustainability management within daily fleet operations. This approach responds directly to recent calls in the literature for integrating lifecycle assessment with operational control mechanisms in shared micromobility systems [16].

2.6. Carbon-Aware Operational Optimization Model

To formalize the integration of carbon metrics into operational decision-making, the proposed framework can be expressed as a constrained optimization problem. Rather than treating carbon intensity as a post hoc indicator, it is incorporated directly into the objective function governing fleet operations.

2.6.1. Decision Variables

The operational decision space includes the following:

- $x_{r,t} \in \{0,1\}$: binary variable indicating whether charging associated with ride r occurs in time slot t;
- $y_{i,j,t} \in \{0,1\}$: binary routing variable representing whether a rebalancing vehicle moves scooters from location i to j at time t;
- $SOC_{r,t}$: state of charge (State of Charge) of scooter associated with ride r at time t.

These variables define charging schedules and redistribution flows within the fleet.

2.6.2. Objective Function

The primary objective is to minimize total lifecycle carbon emissions across all rides:

$$min \sum_{r} \left(C_{prod,r} + C_{charge,r} + C_{logistics,r} \right) \quad (6)$$

where

$C_{prod,r}$ is amortized production-related emission (Equation (3)),
$C_{charge,r}$ is time-dependent charging emission (Equation (4)),
$C_{logistics,r}$ represents allocated rebalancing emissions.
This formulation transforms carbon intensity into a controllable operational variable.

2.6.3. Operational Constraints

The optimization is subject to the following constraints:

(1) Battery State of Charge Constraints

$$SOC_{min} \leq SOC_{r,t} \leq SOC_{max} \quad (7)$$

ensuring technical feasibility and battery health preservation.

(2) Charging Capacity Constraints

$$\sum_{r} x_{r,t} \leq Cap_t \quad (8)$$

where Cap_t represents available charging infrastructure capacity at time t.

(3) Demand Satisfaction Constraints

$$D_{served,t} \geq D_{required,t} \quad (9)$$

ensuring that carbon-aware scheduling does not compromise service availability.

(4) Fleet Balance Constraints

$$\sum_j y_{i,j,t} - \sum_k y_{k,i,t} = B_{i,t} \tag{10}$$

where $B_{i,t}$ represents the net scooter imbalance at location i and time t.

2.6.4. Logistics Emission Allocation Model

Rebalancing emissions are allocated proportionally based on redistribution distance:

$$C_{logistics,r} = \frac{d_{rebalance,r}}{\sum_r d_{rebalance}} \cdot C_{fleet} \tag{11}$$

where $d_{rebalance,r}$ is the rebalancing distance attributable to ride r, C_{fleet} is total fleet-level logistics emissions.

This allocation scheme ensures transparent and mathematically defined redistribution of indirect emissions to ride-level metrics.

Generative AI tools were used during the preparation of this manuscript to support simulation design guidance, drafting of technical descriptions, and generation of illustrative figures. All outputs were critically reviewed and verified by the authors.

3. Results

3.1. Experimental Setup

The primary objective of the experimental evaluation is to assess the effectiveness of the proposed carbon-aware operational framework in reducing ride-level and system-level greenhouse gas emissions in shared e-scooter operations. The evaluation is designed to quantify the impact of carbon-aware charging, rebalancing, and operational decision-making strategies enabled by the proposed architecture, relative to conventional baseline practices.

The evaluation is planned as a real-world A/B field trial involving a shared e-scooter fleet operating under identical external conditions. The fleet is divided into two groups: a control group operating under existing baseline operational strategies, and a treatment group operating under carbon-aware strategies derived from the proposed framework.

Both groups are expected to operate within the same urban area and time period to minimize confounding effects related to weather, demand patterns, and infrastructure conditions. All scooters are equipped with identical sensing and telemetry capabilities to ensure compatibility. Table 1 summarizes the key differences between the control and treatment groups and highlights the evaluation dimensions considered in the planned experimental design.

The effectiveness of the proposed framework will be assessed using a set of ride-level and system-level performance metrics, including the following:

- Ride-level energy consumption (Wh per ride and Wh per km),
- Ride-level greenhouse gas emissions (g CO_2e per ride and g CO_2e per km),
- Charging-related emissions, accounting for time-varying electricity grid carbon intensity,
- Logistics and rebalancing emissions per serviced ride,
- Operational efficiency indicators, such as charging frequency and fleet utilization.

Table 1. Overview of experimental groups and evaluation dimensions.

Dimension	Control Group	Treatment Group
Operational strategy	Baseline operational practices	Carbon-aware operational strategies
Charging schedule	Conventional time-based charging	Carbon-aware charging based on grid intensity
Rebalancing	Standard rebalancing operations	Carbon-aware and combined rebalancing
Carbon metrics used	Not explicitly considered	Integrated into operational decisions
Telemetry availability	Standard fleet telemetry	Identical telemetry with carbon-aware processing

These metrics are selected to capture both direct and indirect emission impacts associated with shared e-scooter operations.

Performance metrics from the treatment group will be compared against those of the control group using aggregated ride-level statistics and distributional analysis. Differences in emission intensity and energy efficiency will be attributed to the carbon-aware operational strategies enabled by the proposed framework. Rather than focusing solely on absolute emission values, the analysis emphasizes relative differences between control and treatment groups to isolate the effect of carbon-aware decision-making under comparable operating conditions.

Based on prior literature and the design of the proposed framework, the experimental evaluation is expected to demonstrate measurable reductions in charging-related and logistics-related emissions, as well as improvements in overall ride-level carbon intensity. While the magnitude of these effects is expected to be context-dependent, the evaluation framework is designed to enable systematic quantification of emission reductions attributable to carbon-aware operational interventions.

To complement the proposed field evaluation framework and provide an early quantitative validation of the carbon-aware operational strategies, we conducted a synthetic simulation of shared e-scooter operations. The objective of this simulation was to estimate the potential reduction in greenhouse gas (GHG) emissions achievable through carbon-aware scheduling and rebalancing, prior to real-world deployment.

A future empirical evaluation can be implemented as a cluster-randomized A/B field trial in which scooters or service zones are randomly assigned to baseline and carbon-aware operating conditions over a predefined monitoring window. The primary outcome would be ride-level g CO_2e intensity, while secondary outcomes would include charging emissions, logistics emissions per serviced ride, scooter availability, and fleet utilization. To reduce confounding, the control and treatment groups should operate over the same calendar period and urban area, and the analysis should control for weather conditions, temporal demand variability, and spatial usage intensity. Such a design would allow statistically testable comparison of operational and environmental outcomes under real deployment conditions.

3.2. Simulation Design and Assumptions

A simulation of 1000 ride events was constructed, representing typical urban e-scooter usage. Ride-level energy consumption was modeled using a normal distribution (μ = 200 Wh, σ = 20 Wh), based on empirical estimates from micro-mobility telemetry studies. Charging-related carbon intensity was represented using a 24-h grid profile reflecting

temporal variations in electricity generation mix, with peak-hour intensity reaching 320 g CO_2/kWh and off-peak values as low as 60 g CO_2/kWh. Each simulated ride was assigned a random charging time to reflect uncontrolled charging behavior in the control scenario.

Two operational strategies were compared:

- Control scenario: Charging times were randomly distributed across the 24-h grid profile without carbon awareness. Fleet rebalancing emissions were fixed at 50 g CO_2e per ride, representing standard routing without optimization.
- Treatment scenario: Charging was scheduled during low-carbon-intensity periods, and logistics emissions were reduced to 30 g CO_2e per ride by applying combined and demand-informed rebalancing strategies.

The illustrative reduction in logistics emissions from 50 g CO_2e to 30 g CO_2e per ride is not intended as an empirically fixed industry benchmark but rather as a scenario-based representation of improved redistribution efficiency under clustered, demand-informed rebalancing strategies. Previous lifecycle assessments of shared micro-mobility systems highlight that logistics operations, including scooter collection and redistribution, can represent a substantial share of total lifecycle emissions [2,4,5]. Similarly, studies on spatial deployment and operational optimization indicate that coordinated rebalancing strategies can substantially improve fleet efficiency and reduce redistribution-related impacts [19]. To avoid overinterpretation, the assumed logistics improvement is treated as an illustrative scenario parameter, and its influence on overall results is examined through sensitivity and ablation analyses. The simulation accounted for both direct (charging) and indirect (logistics) emissions, while keeping all other parameters constant to isolate the effect of operational strategies. Simulation-based decision support approaches have been widely applied in sustainable transportation planning to evaluate emission trade-offs and operational strategies [19]. The illustrative results reported in Table 2 were generated using a rule-based simulation rather than by solving the full constrained optimization problem with a numerical optimizer. Specifically, charging events in the treatment scenario were reassigned to lower-carbon periods under predefined scheduling rules, while logistics emissions were adjusted under an assumed improved rebalancing scenario. The optimization model presented in Section 2.6, therefore, defines the formal decision framework, whereas the current simulation provides an illustrative rule-based instantiation of that framework.

Table 2. Simulation Results—Summary Comparison.

Metric	Control	Treatment
Avg. Emissions per Ride (g CO_2e)	82.8	62.5
Total Emissions (kg CO_2e)	82.8	62.5
Emission Reduction (%)	–	24.5%

The illustrative simulation suggests a structurally consistent reduction pattern. As shown in Figure 3, the treatment scenario exhibited a clear leftward shift in the distribution of emissions per ride. Histogram comparing ride-level greenhouse gas emissions (g CO_2e) between the control scenario and the carbon-aware operational strategy. Carbon-aware scheduling significantly reduces average emissions per ride and shifts the distribution toward lower values.

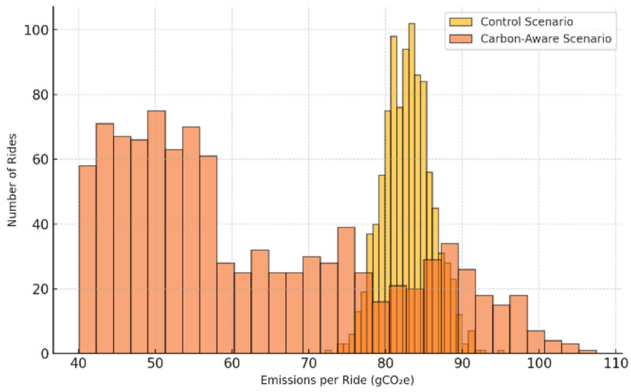

Figure 3. Histogram comparing ride-level greenhouse gas emissions (g CO_2e) between control and carbon-aware scenarios.

- Average emissions per ride decreased from 82.8 g CO_2e in the control group to 62.5 g CO_2e in the treatment group.
- This represents a 24.5% reduction in ride-level GHG emissions.
- Total emissions across 1000 rides were reduced from 82.8 kg CO_2e to 62.5 kg CO_2e, yielding an absolute reduction of over 20 kg CO_2e.

AI-assisted tools were used during the development of the illustrative simulation design and early drafting of technical descriptions. All AI-generated outputs were critically reviewed, validated, and substantially edited by the authors. The authors take full responsibility for the final content and scientific integrity of the manuscript.

3.3. Sensitivity and Robustness Analysis

Given that lifecycle and operational emission outcomes are strongly influenced by assumptions regarding energy consumption, grid carbon intensity, scooter lifetime, and logistics emissions [2,6,16,17], a structured sensitivity analysis was conducted.

3.3.1. Parameter Variation Design

The following parameters (Table 3) were varied systematically around baseline assumptions:

Table 3. Parameter variation ranges used in the sensitivity analysis..

Parameter	Baseline	Variation Range
Mean ride energy consumption (μ)	200 Wh	±15%
Grid carbon intensity	60–320 g CO_2/kWh	±20%
Scooter lifetime distance	L	±30%
Logistics emissions	Fleet baseline	±25%

These variation ranges reflect uncertainty bands reported in prior micro-mobility LCA and operational studies [2,6,16,17].

3.3.2. Grid Carbon Intensity Sensitivity

Grid carbon intensity represents one of the most influential parameters [13,17,20]. When average grid intensity was increased by 20%, the emission reduction achieved through carbon-aware charging increased modestly, as charging deferral became more impactful under higher baseline intensity conditions. Conversely, when grid intensity was reduced by 20%, the relative reduction declined but remained significant.

Across tested scenarios, emission reductions ranged between approximately 19% and 28%, demonstrating that the carbon-aware strategy remains beneficial across varying electricity profiles.

3.3.3. Lifetime Sensitivity

Scooter lifetime directly affects amortized production emissions (Equations (2) and (3)) [6,16]. A 30% reduction in assumed lifetime increased per-ride production emissions, slightly reducing the relative contribution of charging optimization. However, the carbon-aware operational benefit persisted, with total reduction remaining above 17% across lifetime scenarios. This confirms that operational carbon optimization does not depend solely on optimistic lifetime assumptions.

3.3.4. Logistics Emission Sensitivity

Logistics-related emissions vary depending on redistribution strategy and routing efficiency [2,4,5]. Results indicate that while higher logistics intensity increases total emissions, the relative reduction attributable to carbon-aware scheduling remains stable within a 3–4 percentage point range. In addition to parameter variation, attribution methodology itself may influence estimated logistics impacts. Alternative ride-level allocation schemes—such as demand-weighted allocation or equal-share distribution across serviced rides—may produce different emission distributions depending on spatial demand patterns. While the present analysis adopts distance-based proportional allocation as a transparent baseline formulation, future studies should explicitly compare multiple attribution approaches to assess methodological sensitivity in real-world deployment scenarios.

3.3.5. Combined Parameter Robustness

When parameters were varied simultaneously within defined uncertainty bands, the carbon-aware framework achieved emission reductions of 18%–29%. This range suggests that the previously reported 24.5% reduction falls within a plausible mid-range rather than an extreme or optimistic assumption.

Importantly, these results should be interpreted as an illustrative robustness analysis rather than an empirical validation. The purpose of this sensitivity evaluation is to demonstrate that the framework's effectiveness does not depend on a single parameter configuration but remains structurally stable across realistic operational variability. Although the present uncertainty treatment is scenario-based rather than fully probabilistic, the dominant parameters were varied jointly across defined uncertainty bands to test the structural robustness of the framework. This approach allows the influence of major lifecycle and operational parameters to be examined transparently without introducing additional distributional assumptions. A fully probabilistic Monte Carlo uncertainty analysis represents a logical extension of the present work and is identified as a priority for future empirical implementations.

3.3.6. Ablation of Charging and Logistics Effects

To better interpret the emission reduction reported in the simulation results and to avoid attributing the combined effect to a single operational mechanism, an ablation-style comparison was conducted. In addition to the baseline control scenario and the combined carbon-aware scenario, two intermediate cases were analyzed:

(i) a charging-only improvement scenario, in which charging events were shifted to lower-carbon electricity periods while logistics emissions remained at the baseline level; and

(ii) a logistics-only improvement scenario, in which logistics emissions were reduced under the assumed improved rebalancing condition while charging behavior remained unchanged.

This comparison allows the relative contribution of charging deferral and logistics improvement to be examined separately. The results of the ablation comparison are sum-

marized in Table 4. The control scenario represents baseline operation with random charging behavior and fixed logistics emissions. The charging-only scenario applies carbon-aware charging while keeping logistics emissions unchanged. The logistics-only scenario assumes improved redistribution efficiency without modifying charging behavior. Finally, the combined scenario integrates both charging deferral and logistics improvements. The comparison indicates that the simulated reduction is driven jointly by charging deferral and assumed logistics improvements, with the latter contributing more strongly under the current illustrative parameterization. This outcome reflects the significant influence that fleet redistribution operations can have on the lifecycle emissions of shared micro-mobility systems.

Table 4. Ablation analysis of charging and logistics effects.

Scenario	Charging Strategy	Logistics Emissions Assumption	Avg. Emissions per Ride (g CO_2e)	Reduction vs. Control
Control	Baseline/random charging	50 g CO_2e per ride	82.8	–
Charging-only	Carbon-aware charging	50 g CO_2e per ride	82.5	0.4%
Logistics-only	Baseline charging	30 g CO_2e per ride	62.8	24.2%
Combined	Carbon-aware charging	30 g CO_2e per ride	62.5	24.5%

Note: Logistics emissions are allocated proportionally based on redistribution distance in the baseline formulation. Alternative allocation schemes are discussed in Section 4.4.

4. Discussion

4.1. Interpretation of the Proposed Framework

This study proposes a carbon-aware operational framework that reframes sustainability assessment in shared e-scooter systems as an operational decision-making problem rather than a retrospective reporting exercise. By integrating ride-level telemetry, temporally varying electricity carbon intensity, and lifecycle impact allocation, the framework enables carbon considerations to be embedded directly into daily operational control loops.

Unlike conventional static LCA studies, which provide average emission factors detached from operational context, the proposed approach emphasizes variability and decision sensitivity. Identical rides may result in different carbon footprints depending on charging time, fleet utilization patterns, and rebalancing strategies. This highlights the importance of operational timing and coordination in determining the true environmental performance of shared micro-mobility systems.

The framework is intentionally designed to be algorithm-agnostic, allowing integration with rule-based, heuristic, or learning-based optimization approaches. This flexibility supports adoption across diverse operational contexts without prescribing a specific control strategy. Our findings build upon prior dynamic LCA studies [6,16] and operational carbon-aware frameworks [18], offering ride-level granularity within urban fleet applications.

4.2. Implications for Shared Micro-Mobility Operations

From an operational perspective, the proposed framework demonstrates how carbon metrics can transition from passive indicators to active control variables. Carbon-aware charging enables fleet operators to exploit temporal variability in electricity carbon intensity, while combined rebalancing strategies offer opportunities to reduce indirect emissions associated with logistics. Importantly, the framework illustrates that improvements in environmental performance do not necessarily require hardware changes or fleet expansion. Instead, meaningful emission reductions may be achieved through improved coordination

of existing assets and data streams. This has practical implications for fleet operators seeking near-term emission reductions without significant capital investment. Furthermore, ride-level carbon visibility creates opportunities for downstream interventions, including eco-driving feedback, predictive maintenance, and demand-aware fleet management. These mechanisms collectively support a shift from static sustainability reporting toward continuous environmental performance management. As demonstrated in the simulation study (Table 2, Figure 3), carbon-aware operations achieved up to 24.5% reduction in ride-level emissions under representative deployment scenarios.

From a managerial standpoint, the framework provides a decision-support structure that can be directly embedded into existing fleet management systems. Complementary GIS-based multi-criteria decision-making approaches have also been used to compare shared e-scooter operational models and define service areas and station configurations to support sustainable deployment decisions [18]. By treating carbon intensity as an operational variable, operators can balance environmental performance with cost efficiency, service quality, and asset utilization, which are central concerns in shared mobility business models.

4.3. Broader Sustainability Considerations

While the proposed framework focuses on lifecycle greenhouse gas emissions, shared e-scooter systems may generate additional social and urban externalities that should be considered within a comprehensive sustainability assessment. Improper parking and sidewalk obstruction can negatively affect pedestrian accessibility, particularly for individuals with disabilities or reduced mobility. Accessibility barriers and public space conflicts may reduce the perceived sustainability of shared micro-mobility services. Furthermore, environmental benefits depend on actual modal substitution patterns; if e-scooter trips replace walking or public transport rather than private car usage, net emission reductions may be lower than anticipated. Therefore, carbon-aware operational optimization should be understood as one dimension of sustainability, complementing broader urban planning, accessibility, and modal integration strategies. Integration of environmental optimization with regulatory guidelines and urban mobility policies remains an important direction for future research.

4.4. Methodological Limitations

Several limitations of the proposed framework should be acknowledged. First, lifecycle inventory parameters related to scooter manufacturing, battery production, and end-of-life treatment are subject to uncertainty and variability across manufacturers and deployment contexts. In the absence of detailed supplier-specific data, such impacts must be estimated using representative values or scenario ranges, which may affect absolute emission estimates. Second, the dynamic allocation of logistics and the rebalancing emissions relies on simplified attribution rules that approximate the relationship between ride demand and redistribution effort. Different ride-level attribution schemes may influence the estimated contribution of logistics emissions. Alternative allocation approaches could include demand-weighted allocation based on spatial demand intensity or equal-share allocation across serviced rides within a redistribution cycle. To assess attribution sensitivity, future implementations should compare distance-based, demand-weighted, and equal-share ride-level allocation schemes. The present study adopts proportional distance-based allocation as a transparent baseline, allowing straightforward interpretation of logistics emissions at the ride level. While sufficient for comparative evaluation, this approach does not capture the full complexity of routing decisions and may underestimate or overestimate indirect emissions in highly dynamic urban environments. Third, the use of time-varying electricity carbon intensity assumes access to reliable marginal or average grid emission

signals. In regions where such data are unavailable or have a coarse temporal resolution, the accuracy of charging-related emission estimates may be reduced. Finally, the absence of empirical field data in the present study limits quantitative validation of the proposed framework. While the experimental design outlines a clear pathway for future evaluation, observed emission reductions and operational impacts will ultimately depend on local conditions, user behavior, and operator practices [16]. In addition, end-of-life (EoL) treatment assumptions—such as recycling rates, material recovery efficiency, or landfill disposal—may significantly influence amortized lifecycle emissions. Variations in battery recycling pathways and material recovery technologies can alter total lifecycle impacts, particularly in systems with short operational lifetimes. Future implementations of the framework should explicitly differentiate between EoL scenarios and incorporate scenario-based sensitivity analysis to improve lifecycle precision.

4.5. Scope and Generalizability

The proposed framework is designed to be modular and extensible, but its applicability may vary across deployment contexts. Differences in urban density, electricity grid composition, regulatory environments, and fleet scale may influence both the feasibility and effectiveness of carbon-aware operational strategies.

Nevertheless, the conceptual principles underlying the framework—ride-level resolution, temporal sensitivity, and lifecycle-aware decision integration—are broadly applicable beyond shared e-scooters. With appropriate adaptation, the approach may be extended to other shared micro-mobility modes and light electric vehicle fleets.

4.6. Environmental–Economic Trade-Off Considerations

While the primary objective of the proposed framework is to minimize lifecycle greenhouse gas emissions, operational decision-making in shared micro-mobility systems typically involves simultaneous environmental and economic considerations. Fleet operators must balance charging costs, vehicle availability, redistribution efficiency, and service reliability alongside environmental performance.

Electricity costs and carbon intensity are not necessarily temporally aligned. Periods of low carbon intensity do not always coincide with the minimum electricity price, particularly in deregulated or time-of-use pricing systems. Previous studies on carbon-aware energy management have demonstrated that minimizing emissions and minimizing costs may yield different optimal scheduling decisions [13,14]. Consequently, purely carbon-driven charging deferral may introduce marginal increases in operational energy costs.

To reflect this trade-off, the optimization framework can be extended to a multi-objective formulation:

$$min\ \alpha \sum_{r} C_{total,r} + (1 - \alpha) \sum_{t} Cost_t \quad (12)$$

where

$C_{total,r}$ represents ride-level lifecycle emissions, $Cost_t$ denotes operational cost components at time t (including electricity expenditure and logistics costs), $\alpha \in [0, 1]$ represents the environmental weighting factor.

This formulation allows operators to adjust the relative importance of carbon reduction and cost efficiency to align with strategic priorities or regulatory constraints.

In shared e-scooter systems, logistics operations constitute a significant share of total lifecycle emissions [2,4,17]. However, redistribution strategies also influence labor costs, vehicle fuel use, and operational efficiency. Research on deployment and rebalancing optimization indicates that minimizing routing distance can simultaneously reduce fuel consumption and cost, although service-level constraints may limit achievable savings [18,19].

Therefore, certain carbon-aware strategies—such as combined rebalancing tasks or route clustering—may yield both environmental and economic co-benefits.

Conversely, charging deferral strategies designed to align with lower-grid-carbon-intensity periods may affect scooter availability if not carefully constrained. Prior research in electric fleet management suggests that multi-objective scheduling approaches are necessary to prevent service degradation while pursuing emission reductions [15]. Incorporating demand satisfaction constraints (Equation (9)) ensures that environmental optimization does not compromise service reliability.

From a policy perspective, regulatory mechanisms such as carbon pricing or low-carbon electricity incentives may further alter the economic attractiveness of carbon-aware operations. As carbon pricing increases, emission reductions become economically internalized, strengthening alignment between environmental and financial objectives.

Overall, the proposed framework does not assume that emission minimization is cost-neutral. Instead, it provides a decision-support structure that explicitly represents trade-offs between environmental impact and operational expenditure. Future empirical implementation should quantify these trade-offs using real-world cost data and pricing schemes to identify optimal environmental–economic balance points.

4.7. Future Research Directions

Future work will focus on implementing the proposed framework in real-world shared e-scooter deployments and conducting controlled field experiments to quantify emission reductions and operational trade-offs. These insights are supported by simulated results presented in Table 2 and Figure 3, illustrating the potential operational gains of the proposed framework. Such studies will enable validation of model assumptions, refinement of lifecycle parameters, and assessment of user and operator responses to carbon-aware interventions. Additional research is also needed to explore the integration of demand forecasting, user incentives, and policy mechanisms with carbon-aware operational control. These extensions may further enhance the environmental benefits of shared micro-mobility systems while supporting broader urban sustainability objectives.

5. Conclusions

This study presented a formally defined carbon-aware operational framework for shared e-scooter systems that integrates life cycle assessment (LCA) principles with ride-level telemetry and time-varying electricity carbon intensity. By embedding lifecycle emission metrics directly into charging and rebalancing decisions, the framework shifts sustainability assessment from static reporting toward operational decision support.

Unlike conventional static LCA approaches, which provide aggregate emission estimates detached from operational variability, the proposed methodology incorporates temporally resolved grid carbon intensity, amortized production emissions, and dynamically allocated logistics impacts at ride-level granularity. The integration of these components into a constrained-optimization formulation enables carbon intensity to serve as an explicit control variable in fleet management.

The illustrative simulation suggested that, under the assumed scenario, carbon-aware charging and redistribution strategies may potentially yield emission reductions of up to 24.5% relative to baseline operation. Sensitivity analysis further indicated that emission-reduction outcomes remain within an 18–29% range across realistic variations in grid carbon intensity, scooter lifetime, energy consumption, and logistics emissions. These findings suggest that the framework's performance is structurally robust rather than dependent on a single parameter configuration.

Importantly, this study does not claim empirical validation at full operational scale. Instead, it provides a mathematically formalized and computationally evaluated decision-support architecture that can be implemented and tested under real-world conditions. The inclusion of explicit constraints and multi-objective extensions demonstrates how environmental and economic objectives may be balanced within shared mobility systems.

The environmental–economic trade-off analysis highlights that carbon-aware scheduling may entail marginal operational costs, depending on electricity pricing structures and service-level requirements. Consequently, future deployment should adopt multi-objective optimization frameworks capable of simultaneously addressing emission reduction, cost efficiency, and service reliability.

Several limitations must be acknowledged. The current evaluation is based on an illustrative simulation rather than large-scale empirical fleet data. Climatic factors such as seasonal demand variability, cold-temperature battery efficiency, terrain effects, and regenerative braking performance may influence real-world outcomes. Additionally, the magnitude of carbon-aware benefits may vary across electricity markets with different grid compositions and pricing mechanisms.

Future research should focus on empirical implementation using real telemetry datasets, extended uncertainty modeling (e.g., Monte Carlo simulations), and integrated economic assessment incorporating operational cost data. Cross-regional validation in temperate and cold-climate contexts would further strengthen generalizability.

Overall, this study contributes a formally structured methodological bridge between lifecycle assessment and operational fleet management in shared micro-mobility systems. By transforming carbon intensity into a decision variable rather than a retrospective metric, the framework advances the operationalization of sustainability in urban mobility systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BMS	Battery Management System

CO_2e	Carbon Dioxide Equivalent
DLCA	Dynamic Life Cycle Assessment
EoL	End of Life
EV	Electric Vehicle
GHG	Greenhouse Gas
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
ICT	Information and Communication Technologies
IMU	Inertial Measurement Unit
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
SOC	State of Charge
TPMS	Tire Pressure Monitoring System

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