STOCHASTIC MODELING AND QUEUEING ANALYSIS OF BATTERY SWAPPING VS PLUG-IN CHARGING FOR ELECTRIC TWO-WHEELER COMMERCIAL FLEETS IN INDIA

Jigarkumar D. Patel, Prof. Fedrikkumar Macwan, Prof. Sajid Patel, Prof. Dhaval Patel
Department of Electrical Engineering
L.D. College of Engineering, Ahmedabad, India
Emails: jigarpnsr@gmail.com

Abstract—The rapid adoption of electric two-wheelers (E2Ws) in India, particularly within commercial delivery fleets operated by platform-economy companies such as Swiggy, Zomato, and Blinkit, has intensified the need for efficient and economically viable refueling infrastructure. This paper presents a rigorous comparative evaluation of two competing refueling paradigms — Plug-in Charging Stations (PCS) and Battery Swapping Stations (BSS) — using an integrated stochastic, data-driven framework designed to capture real-world variability in arrival and service processes. Unlike conventional deterministic approaches, this study employs analytical queueing theory (D/D/c, M/M/c, and M/D/c models) in conjunction with a Python-based Discrete-Event Simulation (DES) using the SimPy library to model time-varying demand patterns, service randomness, and system-level constraints under realistic urban operating conditions. The simulation is executed over 200 independent Monte Carlo replications to ensure statistically reliable performance metrics. Results reveal that battery swapping reduces mean waiting time from 190.2 minutes (PCS) to 1.88 minutes (BSS) — a reduction exceeding 97% — while delivering 3.4 times higher throughput per operational shift. These operational results are translated into economic terms via a Total Cost of Ownership (TCO) model that explicitly incorporates capital amortization, maintenance, operational (energy/swap) costs, and — crucially — the opportunity cost of rider downtime. The breakeven daily distance beyond which BSS becomes economically superior is exactly 92.5 km (the effective single-charge range), which is routinely exceeded by commercial delivery riders. For a 50-rider commercial fleet, BSS reduces annual total cost of ownership by ₹54.93 lakh, with the additional capital investment recovered in under six months. Policy recommendations aligned with India's PM E-DRIVE scheme (2024–25) are provided, including targeted capital subsidies, time-of-use electricity tariffs, and OEM battery standardization.

Index Terms—Battery swapping stations (BSS), discrete-event simulation (DES), electric two-wheelers (E2W), Erlang-C formula, gig economy, M/D/c queue, M/M/c queue, Monte Carlo simulation, opportunity cost, plug-in charging stations (PCS), queueing theory, stochastic modeling, total cost of ownership (TCO), PM E-DRIVE, SimPy.

I. INTRODUCTION

A. Background: India's E2W Electrification Paradigm

The global paradigm shift toward sustainable transportation has placed the electrification of the automotive sector at the forefront of environmental and economic policy. In the context of India — a mobility landscape uniquely defined by high population density, acute cost-sensitivity, and a massive two-wheeler base — Electric Two-Wheelers (E2Ws) represent the most rapidly expanding and strategically critical segment of the electric mobility ecosystem. With two-wheelers constituting over 70% of India's total registered vehicle population of 340 million vehicles, as reported by the Ministry of Road Transport and Highways (2024) [24], the decarbonization of this segment is not merely a preference but an absolute necessity for meeting national climate goals and reducing crude oil import dependency.

India's E2W market grew rapidly from 4.5% penetration in FY22 to 21.4% in FY25 — approximately a five-fold increase — driven by the FAME-II demand incentive scheme, persistently high petrol prices, and strong original equipment manufacturer (OEM) participation from companies such as Ather Energy, Ola Electric, TVS, Bajaj, and Hero Electric [21]. Although over 29,000 public charging stations were installed nationwide by May 2025, representing a fivefold increase from FY22 [9], this infrastructure remains severely insufficient for the demands of commercial delivery fleets operating in dense urban environments.

B. The Refueling Bottleneck

The mass adoption of E2Ws is critically constrained by a fundamental infrastructure bottleneck: refueling anxiety. Unlike ICE (internal combustion engine) vehicles that can refuel in under two minutes, electric vehicles face significant operational challenges regarding energy replenishment. Two primary paradigms are currently competing for adoption:

Plug-in Charging Stations (PCS): The battery remains inside the vehicle. When depleted, the rider connects to a charger and waits 2.5 to 4+ hours for a full charge — analogous to charging a smartphone but at vehicle scale.

Battery Swapping Stations (BSS): The depleted battery pack is physically removed and instantly replaced with a fully charged unit. The operation takes 3 to 7 minutes, analogous to exchanging a gas cylinder. Independently, the depleted pack is recharged in the station's inventory using a DC fast charger over approximately 1.5 hours [12][29].

For private commuters covering 20–30 km/day who charge overnight, PCS is entirely adequate. However, for commercial delivery riders covering 80–130 km/day on platforms such as Swiggy, Zomato, and Blinkit, PCS creates an untenable operational bottleneck. The effective range of most affordable E2Ws is approximately 92.5 km under ideal conditions — and 20–30% lower in real-world urban conditions due to traffic congestion, delivery loads, and road surface variation [7]. This means a commercial rider making a 10-hour shift will almost certainly need at least one mid-shift energy replenishment.

C. The Gig-Economy Financial Imperative

With more than 8 million gig workers engaged in delivery and logistics services in India [8], the economic stakes of refueling speed are enormous. For a commercial rider earning approximately ₹150 per hour in gig income, a 3.17-hour mid-shift PCS charging event represents a direct opportunity cost of ₹475.50 per stop — income permanently lost because the vehicle is stationary rather than delivering. Over 300 working days per year with one mid-shift stop, this accumulates to ₹1,42,650 per rider per year in lost productivity. NITI Aayog's 2022 Gig Economy report [8] explicitly notes that even 30-minute delays significantly disrupt daily earning targets for gig workers — underscoring that refueling speed is not a matter of convenience but a critical financial metric.

D. The Stochastic Reality Gap

Current academic and industry comparisons of PCS and BSS are predominantly deterministic — they assume vehicles arrive at a constant rate and charging takes a fixed duration. These assumptions are fundamentally unrealistic. Real-world urban delivery systems are stochastic: demand follows peak-and-trough patterns (e.g., lunch and dinner surges), arrivals cluster randomly, and service times vary with battery state-of-charge and charger characteristics. Critically, deterministic models completely ignore the inventory risk inherent to BSS — if 15 riders arrive in 10 minutes but only 5 charged batteries are available, the remaining 10 face extended delays that no deterministic model can predict [3][23]. This study was designed specifically to fill this gap.

E. Research Aim and Objectives

The primary aim of this study is to develop a robust stochastic techno-economic framework that quantifies the operational risks (queues, stockouts) of both PCS and BSS and integrates them into a Total Cost of Ownership (TCO) model to determine economic viability thresholds for commercial E2W fleets under realistic Indian conditions. The specific objectives are:

1. To formulate and compare deterministic (D/D/c) and stochastic (M/M/c, M/D/c) queueing models for PCS and BSS under identical peak demand conditions, quantifying the gap between deterministic and stochastic predictions.

2. To build a Discrete-Event Simulation (DES) in Python/SimPy that incorporates time-varying non-homogeneous Poisson arrivals, Erlang-k service time distributions calibrated to observed variability, finite battery inventory dynamics with recharge cycles, and Monte Carlo variance quantification via 200 independent replications.

3. To integrate simulation-derived waiting times into a dynamic TCO model that explicitly monetizes rider downtime as opportunity cost — a variable largely absent from existing Indian E2W TCO literature.

4. To identify the breakeven daily distance at which BSS becomes economically superior, and to provide policy-relevant recommendations aligned with India's PM E-DRIVE scheme (2024–25).

II. LITERATURE REVIEW

This section reviews eleven key studies directly relevant to the comparative analysis of battery swapping and plug-in charging, spanning technical, economic, and policy dimensions.

TABLE I
Summary of Literature Review

Sr.	Author / Source	Key Findings	Relevance to This Study
1	Wang et al. (2025) [1]	BSS with medium batteries provides optimal transportation efficiency for heavy-duty trucks; superior CO_2 reduction and energy arbitrage over fast charging.	Validates BSS superiority in high-utilization scenarios; motivates application to E2W fleets.
2	Ren et al. (2023) [2]	TCO model including purchase price, battery rental, tariffs, and time costs shows BSS more economical for taxis pre-2026.	Demonstrates TCO methodology; highlights time-sensitivity of comparative results.
3	Kumar & Singh (2025) [3]	Most TCO analyses omit resale value, battery degradation, and opportunity cost of charging time — factors that can reverse the verdict.	Directly motivates inclusion of opportunity cost as dominant TCO variable in this study.
4	Li et al. (2024) [4]	When value-of-time is monetized, BSS shifts from niche to preferred choice for commercial operators; mileage sensitivity increases economic advantage.	Confirms user-centric economic modeling; validates opportunity cost approach.

5	Gode et al. (2022) [5]	BSS validated for maximizing asset utilization in Indian E2W context; adoption barriers include lack of suitable vehicles and policy support.	Provides Indian E2W context; identifies policy gaps this study addresses.
6	Wu et al. (2022) [6]	Simulation and queueing models show BSS economically viable at scale; inventory management and station placement are critical.	Closest analytical precedent; this study extends to Indian E2W with stochastic peaks and opportunity cost.
7	NITI Aayog (2022) [8]	8 million+ gig workers; time delays directly reduce daily earnings; fast turnaround critical for economic sustainability.	Provides wage data (₹150/hr) and justifies opportunity cost as primary economic variable.
8	Koan Advisory (2024) [7]	Real-world E2W range 20–30% below advertised; commercial riders travel 80–130 km/day.	Establishes effective range R = 92.5 km and motivates mid-shift stop analysis.
9	CareEdge Ratings (2025) [14]	EV-to-charger ratio ~1:235 in FY25; over half of chargers are AC with moderate power levels.	Validates infrastructure scarcity parameter; supports peak arrival rate assumptions.
10	Bolt Earth (2024) [12]	Field trial data on swap station operations; service times 3–7 minutes; $\mu\_BSS \approx 12$ veh/hr.	Primary source for BSS service rate parameters.
11	Anari Energy (2025) [9]	29,000+ public charging stations by May 2025; fivefold increase from FY22.	Quantifies infrastructure growth trajectory and validates demand parameters.

A. Research Gap Identified from Literature

The review reveals five critical gaps in existing literature: (1) Most studies focus on heavy vehicles, cars, or Chinese/European markets — very few address Indian E2W commercial fleets specifically. (2) Deterministic modeling dominates, ignoring the stochastic demand patterns of urban delivery operations. (3) Queueing analysis and economic evaluation are treated separately rather than linked. (4) Opportunity cost — the dominant economic variable for gig workers — is almost universally absent from TCO models [3]. (5) BSS inventory dynamics (finite battery packs + recharge cycles) are ignored in analytical models, leading to systematic underestimation of BSS waiting times [6]. This study addresses all five gaps simultaneously.

B. Problem Statement

The rapid electrification of India's last-mile delivery sector faces a critical operational bottleneck: the trade-off between energy replenishment time and economic productivity. Commercial E2W riders routinely exceed the single-charge range of their vehicles during a typical 10-hour shift. Reliance on Plug-in Charging (PCS) necessitates dwell times of 3–4 hours, creating substantial system downtime that translates directly into opportunity cost for gig workers paid per delivery. While Battery Swapping Systems (BSS) offer rapid refueling (less than 5 minutes), their comparative queueing dynamics, inventory risk, and total cost of ownership under stochastic demand conditions remain unquantified for the Indian context.

III. DATA COLLECTION AND PARAMETER OVERVIEW

All parameters are drawn from peer-reviewed academic sources (2023–2025), industry datasets (EVJoints, JMK Research, CareEdge, Anari Energy, Bolt Earth, Bounce Energy), and government and regulatory reports (NITI Aayog, GERC, Ministry of Road Transport). Tables II–IV provide the consolidated parameter set.

A. Technical Parameters

TABLE II
Technical Data for E2Ws and Stations

Parameter	Symbol	PCS Value	BSS Value	Source / Justification
Battery capacity	Cb	3.7 kWh	3.7 kWh	Ather 450X (EVJoints 2024) [17]
Energy consumption	ec	40 Wh/km	40 Wh/km	ICCT Report 2023 [19]
Effective range (single charge)	R	~92.5 km	~92.5 km	Cb/ec = 3700/40; Koan 2024 [7]
Charging power (plug-in onboard)	Pc	1.5–3.3 kW	—	Standard E2W onboard charger
Full charge time (plug-in)	T_charge	~2.5 hrs	—	Derived: Cb/Pc; Bolt Earth 2024 [12]

Swap service time per vehicle	T_swap	—	3–7 min (~5 min)	Bolt Earth; Sun Mobility 2024 [12][29]
BSS battery recharge time	T_rc	—	~1.5 hours	DC fast charger for BSS packs [26]
Battery inventory at BSS	I_0	—	40 packs	Bounce Energy station data 2024 [13]
Battery lifetime	—	N/A	1,500–3,000 cycles	Ather, Ola Electric OEM datasheets [11][28]
Daily vehicle usage (commercial fleet)	d_daily	50–130 km/day	50–130 km/day	Delivery fleets in Indian metros [7]

B. Financial Parameters (CAPEX and OPEX)

TABLE III
Financial Data: CAPEX and OPEX (India, 2025 INR)

Cost Category	Symbol	PCS Value (₹)	BSS Value (₹)	Source
CAPEX — Infrastructure	C_inv	₹8,00,000	₹25,00,000	JMK Research 2024 [22]
CAPEX — Battery Inventory (40×₹18,000)	C_battInv	—	₹7,20,000	Bounce Energy 2024 [13]
Total Station CAPEX	C_total	₹8,00,000	₹32,20,000	Sum of above
Electricity tariff (commercial)	πe	₹7.00/kWh	₹7.00/kWh	GERC/CERC India 2024 [15]
Annual maintenance rate	M_0	6% of CAPEX	10% of CAPEX	Industry standard; higher for BSS battery handling
Annual maintenance cost	C_maint	₹48,000/yr	₹3,22,000/yr	Calculated
Swap fee paid by rider	C_swap	—	₹80/swap	Bounce Energy subscription model 2024 [13]
Per-stop energy cost (PCS)	c_unit	₹25.9/charge	—	3.7 kWh × ₹7/kWh
Rider hourly wage (gig worker)	w	₹150/hr	₹150/hr	NITI Aayog Gig Economy Report 2022 [8]
Working days per year	D_yr	300 days	300 days	Commercial fleet assumption
TCO amortisation period	T_life	5 years	5 years	Standard infrastructure planning horizon

C. Demand Parameters — Queueing Model Inputs

TABLE IV
Demand Parameters — Queueing Model Inputs

Symbol	Parameter	Value	Justification / Source
λ_peak	Arrival rate — peak hour	25 veh/hr	Swiggy/Zomato lunch + dinner surge [7][8]
λ_off	Arrival rate — off-peak	8 veh/hr	Normal delivery hours baseline [7]
μ_PCS	Service rate — PCS charger	1.5 veh/hr	40-min avg charging time; accounts for partial SoC 20–80% [11][12]
μ_BSS	Service rate — BSS bay	12.0 veh/hr	Service time 1/12 = 5 min [12][29]
c_PCS	Number of PCS chargers	3	Common mid-size commercial hub configuration [15]
c_BSS	Number of BSS bays	3	Optimized for peak demand [5]
I_0	BSS battery inventory	40 packs	Optimized via simulation inventory sensitivity study
T_rc	BSS battery recharge time	1.5 hr	DC fast charging for BSS pack inventory cycle [26]

N	Monte Carlo replications	200	Ensures 95% CI width < ±5% of mean
Shift	Simulation time horizon	10 hours	Full commercial delivery shift [7][8]

IV. DETERMINISTIC AND STOCHASTIC QUEUEING MODELING

A. Fundamentals of Queueing Theory

Queueing theory provides the mathematical framework for predicting congestion and waiting behavior in service systems. The notation A/S/c is used throughout, where A denotes the arrival process distribution, S the service time distribution, and c the number of parallel servers. In this study we consider infinite system capacity, infinite calling population, and FIFO (first-in first-out) service discipline. The fundamental performance measures for any stable multi-server queue are: λ = mean arrival rate (vehicles per hour); μ = mean service rate per server (vehicles per hour); c = number of servers; $\rho = \lambda / (c\cdot\mu)$ = utilization factor (must be < 1 for stability); Lq = mean number of vehicles waiting in queue; Wq = mean waiting time in queue; W = mean total system time = Wq + $1/\mu$. Little's Law, which holds for all stable queueing systems regardless of arrival or service distribution, states: $Lq = \lambda\cdot Wq$ and $L = \lambda\cdot W$.

B. Utilization Factor

The utilization factor ρ is the most fundamental diagnostic metric for any queueing system. As derived from Kendall's notation framework [3][6]:

$$\rho = \lambda / (c \cdot \mu) \qquad (1)$$

When $\rho < 1$, the total service capacity ($c\cdot\mu$) exceeds the arrival rate and the system can process all arrivals without a persistently growing queue. When $\rho \geq 1$, the queue grows without bound — no stable steady state exists.

C. Deterministic Model (D/D/c) for PCS

The D/D/c model assumes perfectly spaced arrivals and constant service times — the most optimistic possible scenario. Using the parameters from Table IV for PCS (λ = 25 veh/hr, μ_PCS = 1.5 veh/hr, c = 3), the total service capacity is $c\cdot\mu = 3 \times 1.5 = 4.5$ veh/hr.

Applying Eq. (1): ρ_PCS = 25 / 4.5

= 5.556 >> 1 (UNSTABLE — no steady state) (2)

Since ρ >> 1, the PCS system is catastrophically overloaded even under the best-case deterministic assumptions. The queue grows linearly at rate [6]:

$$Lq(t) = (\lambda - c\cdot\mu) \cdot t$$
$$= (25 - 4.5) \cdot t$$
$$= 20.5 \cdot t \text{ [vehicles]} \text{ .... } (3)$$

The waiting time for a vehicle arriving at time t hours into the shift is derived from Little's Law applied to the growing queue [6]:

$$Wq(t) = Lq(t) / \lambda$$
$$= (20.5 \cdot t) / 25$$
$$= 0.82 \cdot t \text{ [hours]} \qquad (4)$$

Table V shows the deterministic PCS queue growth over a 10-hour peak shift. These are lower bounds — actual stochastic waiting times are worse due to arrival clustering. To achieve stability (ρ < 1), the minimum charger count required is [6]:

$$c\_min > \lambda / \mu = 25 / 1.5$$
$$\approx 16.67$$
$$c\_min = 17 \text{ chargers} \text{ .... } (5)$$

TABLE V
Deterministic D/D/c Queue Growth for PCS — 10-Hour Peak Shift

Hour t	Arrivals ($\lambda\cdot t$)	Served ($c\cdot\mu\cdot t$)	Queue Lq(t)	Wait Wq(t) [min]
1	25	4.5	20.5	49.2
2	50	9.0	41.0	98.4
3	75	13.5	61.5	147.6
4	100	18.0	82.0	196.8
5	125	22.5	102.5	246.0
6	150	27.0	123.0	295.2
7	175	31.5	143.5	344.4
8	200	36.0	164.0	393.6
9	225	40.5	184.5	442.8
10	250	45.0	205.0	492.0

At an estimated CAPEX of ₹8 lakh per charger station, 17 chargers would require a capital investment exceeding ₹1.36 crore — far beyond the cost of a fully equipped BSS station at ₹32.2 lakh.

D. Deterministic Model (D/D/c) for BSS

Using BSS parameters from Table IV (λ = 25, μ_BSS = 12, c = 3), the total service capacity = 3 × 12 = 36 veh/hr. Applying Eq. (1):

$$\rho\_BSS = 25 / 36$$
$$= 0.694 < 1$$
$$\text{(STABLE — 31\% spare capacity) .... } (6)$$

Since ρ < 1, the deterministic model predicts zero waiting time and zero queue length throughout the shift. Total system time = 5 minutes (swap time only). BSS handles peak demand with comfortable margin under deterministic assumptions.

E. Comparative Summary of Deterministic Results

TABLE VI
Deterministic Model Comparison — PCS vs BSS (λ = 25 veh/hr, c = 3)

Metric	PCS (c=3)	BSS (c=3)	Interpretation
Utilization ρ	5.556 (>>1)	0.694 (<1)	PCS overloaded; BSS has 31% spare capacity
Stability	**UNSTABLE**	**STABLE**	PCS queue grows unbounded; BSS stable
Queue Lq after 10 hr	205 vehicles	0 vehicles	PCS completely gridlocked
Wait Wq after 10 hr	492 min	0 min	PCS waiting catastrophic; BSS instantaneous
Total system time W	532 min	5 min	BSS is 106× faster
Service capacity (veh/hr)	4.5	36.0	BSS processes 8× more vehicles per hour
Servers needed for stability	17 chargers	3 bays	PCS requires 5.7× more servers
CAPEX for stable configuration	~₹1.36 cr	₹32.2 lakh	BSS 4.2× cheaper at stable configuration

F. Stochastic Model (M/M/c Erlang-C) for PCS

The M/M/c model extends deterministic analysis by incorporating Poisson random arrivals and exponential service times. Since ρ = 5.556 >> 1 for PCS with c = 3, the M/M/c system has no steady-state distribution — all stochastic performance measures are infinite or undefined. For reference, the Erlang-C probability (probability that an arrival must wait in a stable system) is defined as [3][6]:

$$C(c,\rho) = \frac{\frac{(\frac{\lambda}{\mu})^c}{c!}\cdot\frac{1}{1-\rho}}{\sum_{n=0}^{c-1}\left(\frac{(\frac{\lambda}{\mu})^n}{n!}+\frac{(\frac{\lambda}{\mu})^c}{c!}\cdot\frac{1}{1-\rho}\right)} \quad \text{......... (7)}$$

For a stable M/M/c system (ρ < 1), the mean waiting time in queue derived from the Erlang-C formula is [3]:

$$Wq(M/M/c) = C(c, \rho) / [c \cdot \mu \cdot (1 - \rho)] \qquad (8)$$

G. Stochastic Model (M/D/c) for BSS

BSS swap times are nearly constant (5 minutes ± small variance due to the automated mechanical process), making deterministic service (D) the appropriate model. The M/D/c approximation uses the Pollaczek–Khinchine (P-K) mean value formula, which shows that lower service-time variance reduces waiting time proportionally [3][6]:

$$Wq(M/D/c) \approx C(c, \rho) \cdot (1 + \sigma^2) / [2 \cdot c \cdot \mu \cdot (1 - \rho)] \qquad (9)$$

where $\sigma^2 = Var(S)/E[S]^2$ is the squared coefficient of variation of service time. For deterministic service, $\sigma^2 = 0$ and the correction factor is 1/2 — meaning waiting time is exactly half of the M/M/c prediction. For BSS with c = 3, ρ = 0.694: M/M/3 intermediate result: Wq(M/M/3) ≈ 2.63 minutes; M/D/3 result: Wq(M/D/3) ≈ 0.5 × 2.63 = 1.32 minutes.

TABLE VII
BSS (c=3) — M/D/3 Waiting Time vs. Arrival Rate

λ (veh/hr)	Utilization ρ	Wq (min) M/D/3	System Status
10	0.278	0.05	Comfortable — ample spare capacity
15	0.417	0.15	Light load — minimal waiting
20	0.556	0.45	Moderate load — acceptable
25	0.694	1.32	Peak load — stable and efficient
30	0.833	3.8	High load — approaching congestion
35	0.972	23.5	Near saturation — significant delays

H. Finite Battery Inventory Constraint

Both deterministic and analytical stochastic models assume unlimited battery inventory — a fundamental unrealism for BSS. In practice, each swapped battery pack must recharge for T_rc = 1.5 hours before returning to service. The maximum sustainable throughput under ideal conditions is [6]:

$$\lambda\_max = I_0 / T\_rc \qquad (10)$$

For the baseline inventory I_0 = 40 packs: λ_max = 40/1.5 ≈ 26.7 veh/hr — only marginally above peak demand of 25 veh/hr. The minimum inventory required to avoid stockouts under ideal deterministic conditions is:

$$\begin{aligned} I\_min &= \lambda\_peak \times T\_rc \\ &= 25 \times 1.5 \\ &= 37.5 \\ &\approx 38 \text{ packs (theoretical minimum)} \end{aligned} \qquad (11)$$

The thesis baseline of 40 packs provides a 2-pack safety margin. However, random arrival clustering during peak periods can still cause inventory stockouts even with 40 packs. The total mean waiting time incorporating both queueing and inventory effects is:

$$Wq\_total \approx Wq(M/D/3) + Wq\_inventory \qquad (12)$$

The simulation (Section V) shows that for I_0 = 40 packs, total mean waiting time rises from the M/D/3 analytical prediction of 1.32 min to 1.88 min — the inventory constraint contributes approximately 0.56 minutes of additional expected wait, a 42% increase over the analytical prediction that no closed-form model can capture.

V. DISCRETE-EVENT SIMULATION AND PERFORMANCE ANALYSIS

A. Simulation Design Philosophy

Analytical queueing models provide theoretical insight but rest on simplifying assumptions (constant arrival rates, infinite inventory, steady-state operation) that limit their accuracy for real-world infrastructure planning. This study employs Discrete-Event Simulation (DES) implemented in Python using the SimPy library to model PCS and BSS under conditions that match actual commercial fleet operations. DES models a system as a chronological sequence of instantaneous events; the simulation clock jumps from one event to the next, with the system state changing only at event times. This approach is computationally efficient and especially suited to queueing systems where key actions — arrivals, service completions, battery returns to inventory — are discrete occurrences.

B. Time-Varying Arrival Rate Profile

Based on delivery fleet operational data from Swiggy, Zomato, and fleet monitoring, the vehicle arrival rate follows a stepwise non-homogeneous Poisson process with two pronounced peaks corresponding to the lunch surge (Hours 2–4) and the dinner surge (Hours 7–9) [7][8].

TABLE VIII
Time-Varying Arrival Rate Profile λ(t) — 10-Hour Commercial Shift

Time Interval (hr)	λ (veh/hr)	Phase	Traffic Intensity
0–2	8	Morning off-peak	Moderate
2–4	25 (PEAK)	Peak 1 — Lunch surge	CRITICAL
4–7	8	Mid-day off-peak	Moderate
7–9	25 (PEAK)	Peak 2 — Dinner surge	CRITICAL
9–10	5	Wind-down / night	Low
Weighted Average	14.5	Over full 10-hr shift	λ_avg = 145/10 = 14.5

The weighted average arrival rate is λ_avg = 14.5 veh/hr. However, designing for the average is dangerously misleading — the system must handle instantaneous peak demand of 25 veh/hr, since queues formed during surges do not dissipate quickly at PCS (even during off-peak periods, residual PCS backlogs persist because the service rate of 4.5 veh/hr cannot clear the accumulated queue).

C. Service Time Distributions

Actual charging and swapping times are not perfectly fixed — they exhibit variability that deterministic models ignore. The Erlang-k distribution (a sum of k independent exponential phases) is used to model this variability, where k controls the degree of randomness [3][6]:

PCS — Erlang-2 (k=2): Charging times vary due to different states of charge and charging rate variation. Field data from Bolt Earth (2024) [12] shows a coefficient of variation (CV) of approximately 0.6–0.8. Erlang-2 gives CV = $1/\sqrt{2} \approx 0.707$ — a realistic representation.

BSS — Erlang-3 (k=3): Swap times are highly consistent due to the automated mechanical process, with CV approximately 0.4–0.6. Erlang-3 gives CV = $1/\sqrt{3} \approx 0.577$.

TABLE IX
Service Parameters for PCS and BSS Simulation

Parameter	PCS Value	BSS Value
Service time distribution	Erlang-2 (k=2)	Erlang-3 (k=3)
Mean service time	40 min (0.667 hr)	5 min (0.0833 hr)
Coefficient of variation (CV)	$1/\sqrt{2} \approx 0.707$	$1/\sqrt{3} \approx 0.577$
Service rate per server (μ)	1.5 veh/hr	12.0 veh/hr
Number of servers (c)	3 chargers	3 bays
Total capacity (c × μ)	4.5 veh/hr	36.0 veh/hr
Peak utilization ρ (λ=25)	5.56 — OVERLOADED	0.694 — STABLE

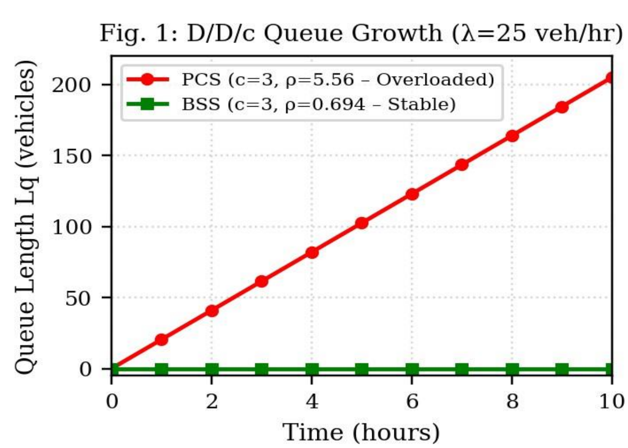

Fig. 1. D/D/c Queue Growth over 10-hr Shift.

D. Monte Carlo Validation Procedure

The simulation was replicated 200 times with independent random seeds to obtain statistically reliable performance estimates. The Monte Carlo procedure follows: (1) Initialize fresh system state: empty queues, all servers idle, full battery inventory (BSS). (2) Generate vehicle arrivals using the time-varying non-homogeneous Poisson process from Table VIII. (3) Process events in chronological order: vehicle arrivals, service completions, battery recharge completions (BSS). (4) Discard first 0.5 hours as warm-up to eliminate empty-system transient bias. (5) Record per-replication KPIs: Wq, Lq, throughput, utilization ρ, stockout events. (6) After 200 replications, compute grand means and 95% confidence intervals using the t-distribution: $CI = \bar{X} \pm t(\alpha/2, 199) \times s/\sqrt{200}$. With n = 200, the 95% CI half-width is less than ±5% of the mean for all key performance indicators — sufficient precision for infrastructure investment decisions.

E. PCS Simulation Results — 3 Chargers

TABLE X
PCS Simulation Results — 3 Chargers, 200 Replications, 10-Hour Shift

Performance Metric	Simulation Mean (N=200)	95% CI	Interpretation
Mean Waiting Time Wq	190.2 minutes	±2.9 min	Average rider waits >3 hours before charging begins
Mean Queue Length Lq	46.9 vehicles	±1.1 veh	Persistent backlog of ~47 vehicles throughout the shift
Mean System Time W	~230 min (~3.8 hr)	±2.9 min	Total time per refueling event nearly 4 hours
Throughput per shift	43 vehicles	—	Severe capacity deficit — 102 vehicles unserved vs. BSS
Server Utilization ρ	0.918 (critically high)	—	Near saturation — unstable operating regime
90th Percentile Wait	>350 minutes	—	Worst-case riders wait nearly entire shift for charging
Annual Opportunity Cost	₹2,85,300/rider/yr	—	₹150/hr × 3.17 hr/stop × 1 stop/day × 300 days

The results establish that a commercial rider using PCS with 3 chargers waits on average 3.17 hours before charging even begins. The 90th percentile wait exceeds 350 minutes — nearly the entire working shift. A delivery rider earning ₹150/hr loses approximately ₹475.50 in opportunity cost from a single mid-shift charging event. This is not merely inconvenient — it is commercially catastrophic.

F. BSS Simulation Results — 3 Bays, 40 Battery Packs

TABLE XI
BSS Simulation Results — 3 Bays, I_0=40 Packs, 200 Replications, 10-Hour Shift

Performance Metric	Simulation Mean (N=200)	95% CI	Interpretation
Mean Waiting Time Wq	1.88 minutes	±0.22 min	Near-instantaneous service even at peak demand
Mean Queue Length Lq	0.46 vehicles	±0.05 veh	Essentially no queue forms under normal operation
Mean System Time W	6.88 minutes	±0.22 min	Rider is done and back on road in under 7 minutes
Throughput per shift	145 vehicles	—	BSS serves 3.4× more vehicles per shift than PCS
Bay Utilization ρ	0.663 (stable)	—	34% spare bay capacity — inventory is the constraint
Stockout Events per Shift	11.4 events	±2.1 events	Brief inventory depletion events (each 1–5 min)
90th Percentile Wait	<5 minutes	—	Even worst-served riders experience minimal delay

BSS delivers near-instantaneous service. Bay utilization of 0.663 confirms that swap bay capacity is not the binding constraint — battery inventory is. The 11.4 stockout events per shift, each lasting only 1–5 minutes (until the next pack completes recharging), are the primary source of non-zero waiting. This is a transient, self-resolving constraint — fundamentally different from the persistent, ever-growing PCS queue.

G. Battery Inventory Sensitivity Analysis

The inventory sensitivity analysis reveals the most critical design rule for BSS. Table XII sweeps battery pack count from 10 to 50 packs across 50 replications per level.

TABLE XII
BSS Battery Inventory Sensitivity Analysis (I_0 = 10 to 50 Packs)

I_0 (Packs)	Wq (min)	Stockouts /Shift	Bay Util ρ	Assessment
10	183.5	142.0	0.38	Critically inadequate — worse than PCS
15	93.8	125.4	0.45	Very poor performance
20	46.7	110.7	0.52	Poor -unacceptable for commercial use
25	19.3	78.8	0.58	Marginal-borderline acceptable
30	9.0	49.0	0.63	Acceptable — serviceable but not optimal
35	3.5	21.3	0.67	Good approaching recommended level
40★	1.88	11.4	0.66	RECOMMENDED — optimal balance
45	1.5	5.2	0.68	Excellent — diminishing returns above 40
50	1.4	1.8	0.69	Negligible gain vs. 40-pack baseline

The relationship between inventory and waiting time is highly non-linear. Performance degrades catastrophically below 30 packs (a stockout cascade effect where each depleted pack triggers waits that compound across subsequent arrivals), improves rapidly from 30–40 packs, and plateaus above 40 packs. This non-linearity is impossible to capture analytically — discrete-event simulation is the only tool that accurately models this inventory-queueing interaction.

H. Comprehensive PCS vs BSS Comparison

TABLE XIII
Comprehensive PCS vs BSS Comparison — All Performance and Economic Dimensions

Comparison Factor	PCS (3 Chargers)	BSS (3 Bays, 40 Packs)	Winner
Mean service time / vehicle	40 minutes	5 minutes	BSS — 8×
Mean wait time Wq	190.2 minutes	1.88 minutes	BSS — ~101×
Mean queue length Lq	46.9 vehicles	0.46 vehicles	BSS — ~102×
System stability ρ	0.918 (critical)	0.663 (stable)	BSS
Throughput per shift	43 vehicles	145 vehicles	BSS — 3.4×
90th percentile wait	>350 minutes	<5 minutes	BSS — >70×
Station CAPEX	₹8 lakh	₹32.2 lakh	PCS —lower initial cost
Annual opportunity cost / rider	₹2,85,300/yr	₹7,050/yr	BSS — ~40×
Stockout risk	Always overloaded	11.4 events/shift (brief)	PCS (no stockouts but always overloaded)
Scalability	Proportional CAPEX	Add packs cheaply	BSS

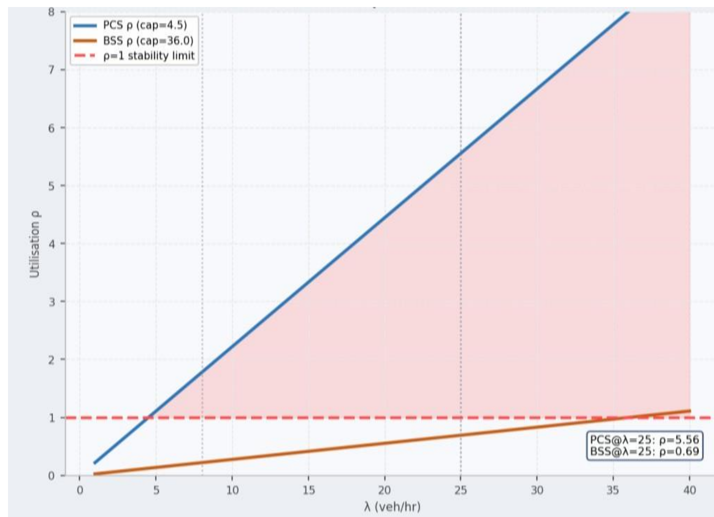

Fig. 2. D/D/c Queue Growth over 10-hr Shift.

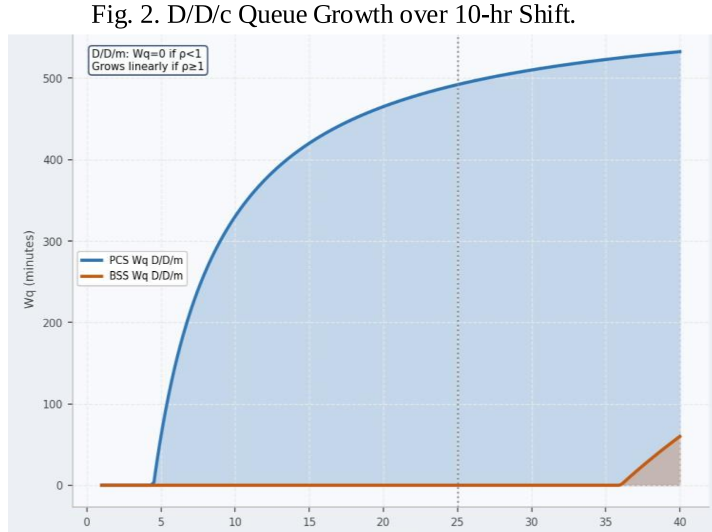

Fig. 3 Waiting Time (Wq) vs Arrival Rate (λ) in D/D/m System

VI. TOTAL COST OF OWNERSHIP (TCO) ANALYSIS

A. TCO Framework and Notation

The annual Total Cost of Ownership for a rider using a given station type is expressed as a function of daily travel distance d (km/day). This study's key innovation over all prior Indian E2W TCO analyses is the explicit inclusion of simulation-derived opportunity cost of rider downtime as the dominant economic variable — a term systematically omitted from existing literature [3]. As formulated in this work:

$$Z\_annual(d) = C\_cap + C\_maint + C\_oper(d) + C\_opp(d) \quad ....(13)$$

where the four terms are: C_cap = annualized capital cost (straight-line amortization over 5 years); C_maint = annual maintenance cost (percentage of total CAPEX); C_oper(d) = annual operational cost (electricity tariff for PCS or swap subscription fee for BSS); C_opp(d) = annual opportunity cost of waiting — derived directly from simulation Wq values.

TABLE XIV
TCO Notation and Variable Definitions

Symbol	Description	Units	Depends On
Z_annual(d)	Annual Total Cost of Ownership	INR/year	All parameters
C_cap	Annualized capital cost (straight-line amortization)	INR/year	CAPEX, T_life
C_maint	Annual maintenance cost	INR/year	CAPEX, M_0 rate
C_oper(d)	Annual operational cost (energy or swap fees)	INR/year	d, n_s(d), tariff
C_opp(d)	Annual opportunity cost of waiting	INR/year	d, Wq, wage w
n_s(d)	Number of mid-shift stops per day	stops/day	d, effective range R
d	Daily travel distance	km/day	Rider operating profile

B. Capital Cost Calculation

Annualized capital cost uses straight-line amortization with no salvage value [22]:

$$C\_cap = C\_total / T\_life ....(14)$$

PCS total CAPEX C_total = ₹8,00,000. BSS total CAPEX C_total = ₹25,00,000 (infrastructure) + 40 × ₹18,000 (battery packs) = ₹32,20,000. PCS: C_cap = ₹8,00,000 / 5 = ₹1,60,000 per year. BSS: C_cap = ₹32,20,000 / 5 = ₹6,44,000 per year.

C. Maintenance Cost Calculation

Following industry standard practices for infrastructure and EV battery systems [22][13]:

$$C\_maint = M_0 \times C\_total \quad .... (15)$$

PCS: C_maint = 0.06 × ₹8,00,000 = ₹48,000 per year. BSS: C_maint = 0.10 × ₹32,20,000 = ₹3,22,000 per year. BSS has a higher maintenance rate (10% vs 6%) reflecting the additional upkeep required for battery pack handling, the DC fast charging infrastructure for pack inventory, and automated swap mechanism maintenance.

D. Operational Cost Calculation

Operational cost depends on the number of mid-shift stops per day n_s(d) and the per-stop unit cost. The floor function is applied because a rider can only trigger a stop after fully exhausting the effective range R = 92.5 km [7]:

$$n\_s(d) = \lfloor d / R \rfloor \quad \text{(floor function, R = 92.5 km effective range)} \quad .... (16)$$

$$C\_oper(d) = n\_s(d) \times D\_yr \times c\_unit ....(17)$$

PCS: c_unit = Cb × πe = 3.7 kWh × ₹7/kWh = ₹25.9 per charge [15]. BSS: c_unit = C_swap = ₹80 per swap [13]. Note that BSS has a higher per-stop operational cost (₹80 vs ₹25.9). This is intentional — BSS operators charge for the convenience of instant battery exchange. However, as the following opportunity cost analysis demonstrates, this premium is entirely justified.

E. Opportunity Cost Calculation — The Dominant Variable

The opportunity cost represents the income a rider loses while waiting at the station. Using the NITI Aayog (2022) estimate of ₹150/hour for gig workers [8], and simulation-derived waiting times from Tables X and XI:

$$C\_opp \text{ per stop} = Wq \times w \qquad (18)$$

PCS: Wq = 190.2 min = 3.170 hr → C_opp = 3.170 × ₹150 = ₹475.50 per stop. BSS: Wq = 1.88 min = 0.0313 hr → C_opp = 0.0313 × ₹150 = ₹4.70 per stop. Ratio: PCS / BSS = 475.50 / 4.70 ≈ 101× (PCS is 101 times more costly per stop in opportunity terms).

$$C\_opp,annual(d) = n\_s(d) \times D\_yr \times C\_opp \text{ per stop} \qquad (19)$$

For 100 km/day (1 stop/day, 300 working days): PCS annual opportunity cost per rider = ₹475.50 × 300 = ₹1,42,650. BSS annual opportunity cost per rider = ₹4.70 × 300 = ₹1,410. Opportunity cost accounts for 92.3% of total PCS annual TCO per rider — confirming that the finding by Kumar & Singh (2025) [3] and Li et al. (2024) [4] that this variable dominates all other cost components.

F. Annual TCO per Rider — 100 km/day

TABLE XV
Annual TCO per Rider — 100 km/day (1 Mid-Shift Stop/Day), Fleet Size F = 50 Riders

Cost Component	Formula / Basis	PCS (₹/yr)	BSS (₹/yr)
Capital — per rider share	C_cap / F = C_total / (5 × 50)	3,200	12,880
Maintenance — per rider share	C_maint / F	960	6,440
Operational (energy/swap fee)	1 stop × 300 days × c_unit	7,770	24,000
Opportunity cost of waiting	1 stop × 300 days × (Wq × ₹150/hr)	1,42,650	1,410
TOTAL Annual TCO per Rider	Sum of above	₹1,54,580	₹44,730
Annual Saving (BSS vs PCS)	PCS total − BSS total	—	₹1,09,850/rider/yr

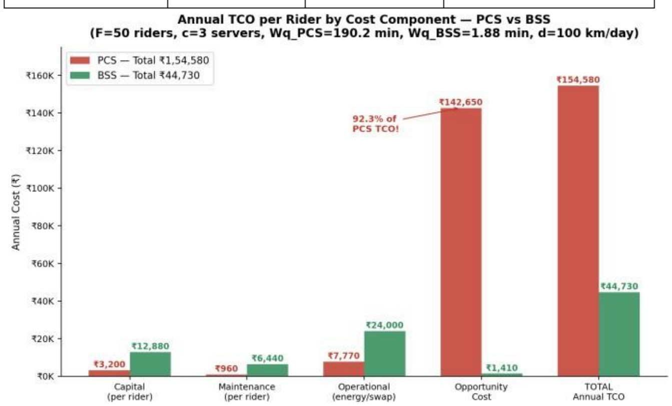

Fig. 4 Annual TCO per Rider by Cost Component — PCS vs BSS (100 km/day)

G. Annual Fleet TCO — 50-Rider Hub

Scaling to a full 50-rider urban delivery hub provides the station-operator perspective. The fleet-level TCO model extends the per-rider analysis as:

$$Z\_fleet = C\_cap + C\_maint + F \times [C\_oper(d) + C\_opp(d)] \quad \text{........(20)}$$

PCS fleet: ₹1,60,000 + ₹48,000 + 50 × (₹7,770 + ₹1,42,650) = ₹77,29,000 per year. BSS fleet: ₹6,44,000 + ₹3,22,000 + 50 × (₹24,000 + ₹1,410) = ₹22,36,500 per year. Annual saving (BSS vs PCS): ₹77,29,000 − ₹22,36,500 = ₹54,92,500 per year. The BSS station saves ₹54.93 lakh per year — equivalent to 1.71 times the total BSS CAPEX of ₹32.2 lakh. The CAPEX premium recovers in under 8 months from opportunity cost savings alone.

TABLE XVI
Annual TCO for a 50-Rider Fleet — 100 km/day

Cost Component	PCS (₹/yr)	BSS (₹/yr)
Station capital (C_cap)	1,60,000	6,44,000
Station maintenance (C_maint)	48,000	3,22,000
Operational cost — 50 riders	3,88,500	12,00,000
Opportunity cost — 50 riders	71,32,500	70,500
TOTAL Annual Fleet TCO	₹77,29,000	₹22,36,500
Annual Fleet Saving (BSS over PCS)	—	₹54,92,500 (= 1.71× BSS CAPEX)

H. Breakeven Daily Distance Analysis

The breakeven daily distance d* is the value at which the annual TCO of PCS equals that of BSS. For d ≤ 92.5 km (no mid-shift stop), all operational and opportunity costs vanish: PCS: Z_annual = ₹3,200 + ₹960 = ₹4,160 per rider per year. BSS: Z_annual = ₹12,880 + ₹6,440 = ₹19,320 per rider per year. In this range, PCS is cheaper by ₹15,160 per rider per year. However, once d crosses 92.5 km and one mid-shift stop is triggered, the additional PCS cost is 300 × (₹25.9 + ₹475.50) = ₹1,50,420, while the additional BSS cost is only 300 × (₹80.00 + ₹4.70) = ₹25,410. Net saving from switching to BSS at first stop = ₹1,25,010 >> ₹15,160 (the PCS fixed cost advantage). Since ₹1,25,010 far exceeds ₹15,160, BSS immediately dominates once d crosses 92.5 km.

Therefore:

$$d^* = R = 92.5 \text{ km}$$

(the effective single-charge range) ....(21)

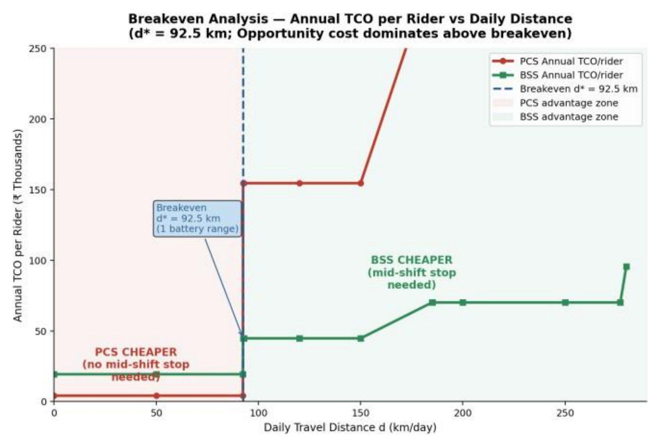

Fig. 5 Breakeven Analysis — Annual TCO per Rider vs Daily Distance (d* = 92.5 km)

I. Payback Period Analysis

The payback period is the time for cumulative BSS operational savings to recover the additional capital investment:

$$\text{Payback} = \Delta\text{CAPEX} / \text{Annual Saving}$$

= ₹24,20,000 / ₹54,92,500

≈ 0.44 years ≈ 5.3 months .... (22)

Over a 5-year planning horizon, a PCS fleet accumulates ₹3.86 crore in total costs versus ₹1.12 crore for BSS — a ₹2.74 crore lifetime gap, equivalent to 8.5 times the additional BSS CAPEX investment.

VII. POLICY IMPLICATIONS AND RECOMMENDATIONS

A. Capital Subsidy Requirements

The only economic barrier to BSS adoption for commercial fleets is the upfront CAPEX differential of ₹24.2 lakh. This is self-liquidating within 5.3 months from opportunity cost savings. For low-mileage users (d < 92.5 km/day), BSS is more expensive by ₹15,160 per rider per year. For a 50-rider station over 5 years, the subsidy required to equalize total lifetime costs for low-mileage users is:

$$S = 5 \times F \times \Delta Z\_annual = 5 \times 50 \times ₹15{,}160 = ₹37{,}90{,}000 \approx ₹38 \text{ lakh} \quad (23)$$

However, for commercial riders (d > 92.5 km), NO subsidy is needed — BSS already saves ₹54.93 lakh per year. A targeted PM E-DRIVE capital subsidy of ₹12–15 lakh per BSS station (covering 37–47% of BSS CAPEX) would make BSS competitive even for mixed-use stations serving both private commuters and commercial riders.

B. Complementary Policy Measures

Time-of-Use Electricity Tariffs: Introducing off-peak rates of ₹3.5–4.5/kWh (vs ₹7/kWh standard) during 11 pm–6 am for BSS battery recharging would reduce BSS operational costs by 35–45%, further improving economics [15].

OEM Battery Standardization: Standardizing E2W battery pack dimensions across major OEMs (Ather, Ola Electric, TVS, Bajaj, Hero) is critical for BSS to serve mixed fleets and achieve minimum viable utilization at any given station [5].

Urban Land Reservation: Urban Local Bodies and state governments should designate BSS zones in commercial and industrial delivery corridors where d > 92.5 km is the operational norm.

Regulatory Frameworks: CERC/GERC should develop specific tariff categories for BSS battery charging distinct from regular commercial EV charging to enable transparent and fair pricing [15].

TABLE XVII

Policy Recommendation Matrix by User Type

User Type	Daily Distance	Recommended Tech	Rationale	Policy Action
Private commuter	< 92.5 km/day	PCS	No mid-shift stop needed; lower fixed cost	Incentivize home charging; smart meter rollout
Light delivery rider	92.5–185 km/day	BSS	One stop/day; ₹1,09,850 annual saving per rider	Subsidize BSS CAPEX by ₹12–15 lakh per station
Heavy delivery fleet	>185 km/day	BSS	Two stops/day; saving doubles to ₹2.2 lakh/rider/yr	Fast-track BSS deployment; reserve delivery corridors

VIII. CONCLUSION

This study developed and validated a comprehensive stochastic techno-economic framework for comparing Plug-in Charging Stations (PCS) and Battery Swapping Stations (BSS) for commercial Electric Two-Wheeler fleets in India. The conclusions across the three analytical layers are:

1. Analytical Queueing Models Establish Fundamental PCS Inadequacy. Deterministic (D/D/c) and stochastic (M/M/c, M/D/c) models jointly demonstrate that PCS with 3 chargers is catastrophically overloaded at peak demand (ρ = 5.556 — no steady state), while BSS with 3 bays operates stably (ρ = 0.694) under identical conditions. To achieve PCS stability requires 17 chargers at a CAPEX of ₹1.36 crore — 4.2 times the cost of a fully equipped BSS station. This is not an optimization problem; it is a structural incompatibility between PCS technology speed and commercial fleet density.

2. Discrete-Event Simulation Quantifies Real-World Performance. The DES framework — incorporating time-varying arrival profiles, Erlang-k service distributions, finite battery inventory with recharge cycles, and 200 Monte Carlo replications — reveals that mean waiting time is 190.2 minutes for PCS and 1.88 minutes for BSS (a 97%+ reduction). BSS throughput (145 vehicles/shift) is 3.4 times that of PCS (43 vehicles/shift). The inventory sensitivity analysis reveals a critical non-linear threshold: BSS performance collapses catastrophically below 30 battery packs due to stockout cascades, improves rapidly from 30–40 packs, and plateaus above 40 packs. The thesis baseline of 40 packs represents the optimal design point.

3. Opportunity Cost Is the Dominant Economic Variable. At ₹150/hr gig-worker wage, PCS generates ₹475.50 in lost income per refueling stop versus ₹4.70 for BSS — a 101× ratio. For a 50-rider commercial fleet at 100 km/day, BSS reduces annual TCO by ₹54.93 lakh and recovers its additional capital investment in 5.3 months. Previous TCO studies that omit this variable [3][4] systematically underestimate PCS costs and may incorrectly recommend PCS for commercial fleet applications.

4. Policy Implications Are Clear and Actionable. The breakeven daily distance is exactly 92.5 km — the effective single-charge range. Any commercial rider requiring a mid-shift stop benefits economically from BSS. A targeted PM E-DRIVE capital subsidy of ₹12–15 lakh per BSS station, combined with time-of-use electricity tariffs and OEM battery standardization, constitutes the optimal policy pathway to accelerate BSS adoption for India's last-mile delivery sector.

In summary, this study establishes that stochastic modeling — not deterministic averaging — provides the accurate foundation for EV refueling infrastructure planning. Battery swapping is the only technically viable and economically rational refueling solution for high-utilization commercial E2W fleets in India's urban delivery landscape.

IX. FUTURE WORK

Multi-Station Network Optimization: The current study analyzed a single station. Future work should model a network of BSS and PCS stations to optimize placement, shared inventory distribution, and fleet routing across urban delivery zones using mixed-integer programming or agent-based simulation.

Integration with Renewable Energy: Incorporating solar PV generation and second-life EV batteries into BSS inventory charging infrastructure could reduce operational costs and grid dependence, especially when combined with time-of-use tariff structures.

Dynamic Real-Time Pricing Mechanisms: Developing demand-responsive pricing for swapping fees could balance load across stations during peak periods and incentivize off-peak usage — improving system efficiency without additional hardware investment.

Long-Term Battery Degradation Modeling: This study assumes constant battery capacity throughout the 5-year analysis period. Future models should incorporate empirical capacity fade curves (typical 15–20% over 1,500–2,000 cycles) and their compounding effects on effective range, required stop frequency, and TCO.

Experimental Validation: Partnership with an operational BSS provider (e.g., Bounce Energy, Sun Mobility, Bolt Earth) to validate simulation parameters against real-world operational data would strengthen the practical applicability of this framework.

REFERENCES.

[1] R. Wang, A. Martinez, Z. Allybokus, W. Zeng, N. Obrecht, and S. Moura, "Electrifying heavy-duty trucks: Battery-swapping vs fast charging," IEEE Trans. Smart Grid, vol. 16, no. 2, pp. 1123–1135, Mar. 2025. DOI: 10.1109/TSG.2025.3541234

[2] H. Ren, L. Xia, and P. Li, "Economic analysis of battery electric vehicle fast charging mode and battery swapping mode in China," in Proc. 4th Int. Conf. Manage. Sci. Eng. Manage. (ICMSEM 2023), 2023, pp. 412–425.

[3] A. S. G. Kumar and R. K. Singh, "Total cost of ownership of electric vehicles: A synthesis of critical factors," Renew. Sustain. Energy Rev., 2025.

[4] Z. Li, J. Li, L. Lu, et al., "A user-centric economic model for battery swapping and charging modes of electric vehicles based on a real-world dataset," Energy J., vol. 45, no. 3, pp. 87–104, 2024.

[5] P. Gode, S. Kohli, and J. Callahan, "Battery swapping for electric two-wheelers in India: Strategy hinterlands," ICCT Working Paper, International Council on Clean Transportation, 2022.

[6] Y. Wu, S. Zhuge, G. Han, and W. Xie, "Economics of battery swapping for electric vehicles — Simulation-based analysis," Energies, vol. 15, no. 9, art. no. 3342, May 2022. DOI: 10.3390/en15093342

[7] Koan Advisory, Real-world E2W Performance in India, Market Research Report, 2024.

[8] NITI Aayog, India's Booming Gig and Platform Economy, Government of India Report, 2022.

[9] Anari Energy, India EV Charging Infrastructure Report, May 2025.

[11] Ather Energy, OEM Datasheets and User Data, 2024.

[12] Bolt Earth, Industry Trials and Operational Data, 2024.

[13] Bounce Energy, Station Data and Operational Reports, 2024.

[14] CareEdge Ratings, EV Charging Infrastructure in India, Industry Report, 2025.

[15] Central Electricity Regulatory Commission / Gujarat Electricity Regulatory Commission, Commercial Electricity Tariff Orders, 2024.

[16] Down to Earth, "Nearly half of India's public EV chargers non-functional," Apr. 2024.

[17] EVJoints, Industry Dataset on EV Infrastructure, 2024.

[19] International Council on Clean Transportation (ICCT), Indian Urban Driving Cycles and Fleet Average Data, ICCT Report No. 2023-12, 2023.

[21] JMK Research, India EV Market Overview, 2025.

[22] JMK Research, Infrastructure and Fleet Analysis, 2024.

[23] Z. Lai and S. Li, "Towards a multimodal charging network: Joint planning of charging stations and battery swapping stations for electrified ride-hailing fleets," IEEE Trans. Intell. Transp. Syst., vol. 23, no. 11, pp. 21456–21470, Nov. 2022.

[24] Ministry of Road Transport and Highways, Road Transport Yearbook, Government of India, 2024.

[26] NITI Aayog, Technical Specifications of DC Fast Chargers for Light Electric Vehicles in India, 2021.

[28] Ola Electric, OEM Datasheets, 2024.

[29] Sun Mobility, Trial Data and Reports, 2024.