

Article

Tri-Level Hybrid Electric Bus Scheduling for Integrated Fleet and Charger Optimization: A Case Study of Madurai District

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Abstract

Public transport corporations in Tamil Nadu face increasing operational and financial pressure due to rising diesel fuel prices, maintenance costs, and operational inefficiencies associated with the conventional bus systems. In many districts, diesel-powered public transport services also suffer from irregular vehicle dispatch and poor timetable adherence, leading to unreliable passenger service. Meanwhile, the rapid penetration of electric two-wheelers and four-wheelers indicates a broader transition towards electrified mobility. Extending electrification to public transport requires prudently designed operational planning, as electric buses operate under battery capacity constraints and charging co-ordination constraints. In such systems, strict adherence to the scheduling of trips and efficient energy management becomes critical for maintaining service reliability. To address these challenges, this study proposes a Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework integrating Particle Swarm Optimization for global search, Rule-Based Scoring Large Neighborhood Search for adaptive schedule improvement, and Mixed Integer Linear Programming for exact repair optimization. The framework simultaneously optimizes fleet size, depot charging infrastructure allocation, and daily bus assignment under timetable constraints. The proposed model has been applied in three interconnected corridors in Madurai District, which are Thirumangalam, Arapalayam, and Mattuthavani, covering 810 scheduled daily timetabled trips between 05:00 AM and 12:30 AM. Computational results show that the hybrid framework has achieved a 2.8% reduction in annual scheduling cost compared to the best conventional optimization method. Furthermore, compared to equivalent diesel-based operations, the optimized electric system has demonstrated approximately 32.3% annual cost savings, confirming the economic viability of integrated fleet-charger scheduling for district-level electric bus deployment.



Academic Editor: Carlos
Llopis-Albert

Received: 18 June 2026

Revised: 6 July 2026

Accepted: 10 July 2026

Published: 15 July 2026

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Keywords: electric bus scheduling; hybrid optimization; PSO; RBS-LNS; MILP repair; fleet and charger planning; cost minimization

1. Introduction

Growing environmental concerns, increasing urban air pollution, and the depletion of fossil fuel resources have accelerated the global transition toward sustainable transportation systems. Public transit agencies are increasingly exploring battery electric buses as an alternative to conventional diesel fleets, due to their potential to significantly reduce greenhouse gas emissions and improve urban air quality. However, the operational characteristics of electric buses introduce new planning challenges, particularly related to battery capacity

limitations, charging infrastructure requirements, and energy management within transit networks. Early studies investigated electric bus deployment from an operational planning perspective, focusing on integrating energy constraints into vehicle scheduling models. One such work formulated an electric vehicle scheduling framework that incorporated battery charging requirements with trip assignment decisions, demonstrating that energy feasibility must be considered alongside the traditional scheduling constraints [1]. Subsequent research extended this concept by integrating charging infrastructure planning with vehicle scheduling through mixed-integer optimization models, showing that coordinated infrastructure planning can significantly reduce operational costs while maintaining service reliability [2].

To address the computational complexity of large transit networks, several studies have explored heuristic and metaheuristic optimization approaches. These methods have been applied to improve fleet utilization and reduce operational costs while satisfying battery energy constraints and charging requirements in large-scale transit systems [3]. Building upon this direction, hybrid optimization models have been proposed to simultaneously determine fleet composition and charging allocation, highlighting the importance of coordinated decisions between operational scheduling and infrastructure deployment [4]. Another stream of research focuses on integrated optimization frameworks for electric bus systems. Multi-objective models have been developed to jointly optimize bus scheduling and charging infrastructure planning, demonstrating that coordinated decision-making improves both operational efficiency and passenger service quality [5]. In parallel, researchers have investigated charging management strategies that consider electricity price variations and grid operational constraints, revealing the potential for significant cost savings through optimized charging schedules [6].

With the increasing electrification of transit fleets, advanced optimization techniques have been adopted to handle complex operational conditions. Large neighborhood search and genetic algorithm-based approaches have been applied to electric bus scheduling problems to efficiently generate high-quality solutions for large transit networks [7]. These studies demonstrate that heuristic methods can effectively address the combinatorial complexity associated with large-scale electric bus scheduling problems. In addition to operational scheduling, the integration of renewable energy sources with electric bus charging systems has attracted growing attention. Research has shown that coordinated charging strategies can enhance renewable energy utilization and reduce electricity consumption from conventional grid sources [8]. Energy-aware scheduling models have also been proposed to integrate public transportation operations with power distribution networks, enabling improved coordination between transport and energy systems [9]. Recent developments have also explored the application of data-driven and machine learning techniques for electric bus operations. These approaches aim to predict operational conditions and dynamically adjust charging schedules to improve system efficiency and reduce computational complexity [10]. Similarly, optimization models have been developed to determine optimal fleet sizes and charging infrastructure investments necessary to support reliable electric transit operations [11]. Several studies have further examined the interaction between charging infrastructure deployment and vehicle scheduling decisions. Mathematical programming models have demonstrated that coordinated planning of fleet operations and charger locations can significantly reduce charging delays and improve fleet utilization [12]. To address operational uncertainties, stochastic optimization approaches have also been proposed to incorporate variations in travel time and energy consumption into scheduling decisions [13].

Energy cost optimization has been another key research focus. Several works have developed charging scheduling models that incorporate time-of-use electricity tariffs and

demand response mechanisms to reduce operational energy costs while maintaining reliable transit service [14]. Similarly, optimization frameworks have been proposed for charging infrastructure planning under uncertain operational conditions, ensuring efficient charger deployment while maintaining service continuity [15]. The integration of renewable energy sources into electric bus charging systems has also been explored extensively. Studies have evaluated the role of solar and wind energy in supporting electric bus charging operations, demonstrating that renewable energy integration can significantly improve sustainability and reduce system costs [16]. More recent research has proposed integrated fleet–infrastructure optimization models to jointly determine vehicle scheduling and charging decisions, further improving operational efficiency [17]. Uncertainty-aware scheduling approaches have also been developed to address variability in operational conditions. Robust optimization models have been proposed to account for fluctuations in energy consumption and passenger demand, improving the reliability of electric bus scheduling solutions [18]. In addition, multi-objective optimization approaches have been applied to balance competing objectives such as operational efficiency, energy cost, and service reliability [19]. To further improve the computational efficiency, hybrid optimization algorithms combining heuristic search and mathematical programming have been introduced for solving large-scale electric bus scheduling problems [20]. Stochastic optimization models have also been proposed to address uncertainties in charging demand and electricity pricing, enabling more reliable operational planning [21].

Charging infrastructure planning remains a critical component of electric bus deployment. Studies have developed integrated models that simultaneously consider transportation network constraints and power system limitations, highlighting the importance of coordinated planning between transit operators and energy providers [22]. Other research has explored the role of renewable energy generation, such as solar power, in supporting electric bus charging infrastructure to enhance sustainability [23]. The interaction between charging infrastructure availability and fleet scheduling decisions has also been investigated, demonstrating that infrastructure limitations significantly affect operational efficiency in electric transit systems [24]. Hybrid optimization frameworks combining heuristic search techniques and mathematical programming have been proposed to improve solution quality and computational performance for complex scheduling problems [25]. Further research has examined scheduling approaches that incorporate passenger demand patterns and charging infrastructure availability to enhance service reliability and operational efficiency [26]. This work addresses multi-depot electric bus scheduling with energy and charging constraints under timetable requirements. It highlights that heuristic methods improve scalability while ensuring operational feasibility [27]. This study proposes a bi-level model integrating charging station location with land-use and transportation interactions. It shows that infrastructure decisions influence demand, accessibility, and overall system performance [28]. This paper optimizes charger placement by considering deadheading, charging capacity, and time constraints. It shows that improper charger allocation leads to higher costs and reduced service efficiency [29]. More advanced scheduling frameworks incorporate energy trading mechanisms and uncertainty management. For instance, robust optimization models have been developed to schedule electric buses and charging stations while considering vehicle-to-grid interactions, renewable energy sources, and electricity price uncertainties, enabling improved operational profitability and system resilience [30]. The increasing penetration of electric vehicles has made the optimal placement of charging infrastructure a critical challenge for sustainable transportation systems. Existing studies mainly employ optimization, GIS, and conventional MCDM approaches, which often struggle to effectively handle uncertainty and decision-making ambiguity [31]. More recently, GeoAI and deep learning frameworks integrating spatial context, EV demand, land-use,

and traffic characteristics have demonstrated significant potential for developing efficient and sustainable EV charging infrastructure [32]. Despite the significant progress achieved in electric bus scheduling research, several challenges remain. Many existing studies address individual aspects of the problem, such as fleet scheduling, charging infrastructure planning, or energy management in isolation. However, in practical transit systems, these decisions are highly interdependent. Moreover, the increasing integration of renewable energy sources and the presence of operational uncertainties further complicate the electric bus scheduling problems, requiring more comprehensive and scalable optimization frameworks. Figure 1, which presents a radar comparison of key methodological capabilities observed in the literature and those incorporated in the proposed TLH-EBS framework, highlights that the proposed approach simultaneously integrates fleet scheduling, charger allocation, hybrid optimization, and multi-level decision mechanisms, which are rarely addressed together in the existing studies.

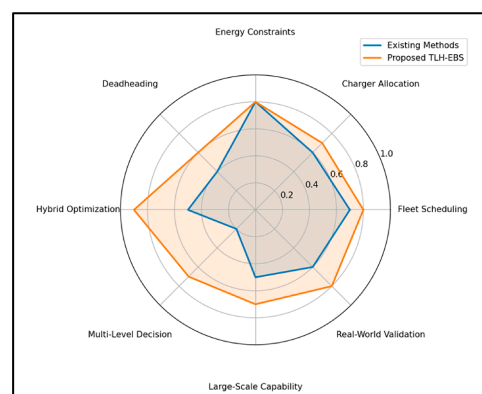


Figure 1. Capability-based comparison of representative electric bus scheduling approaches using eight methodological evaluation criteria.

Table 1 presents a comparative analysis of representative electric bus scheduling studies and the proposed TLH-EBS framework in terms of key algorithmic capabilities. Existing approaches primarily focus on isolated aspects of the problem, such as trip scheduling, charging management, or energy constraint handling. Most studies employ single optimization techniques such as MILP, heuristic algorithms, or stochastic optimization, which limit their ability to simultaneously address multiple operational decisions in large transit networks.

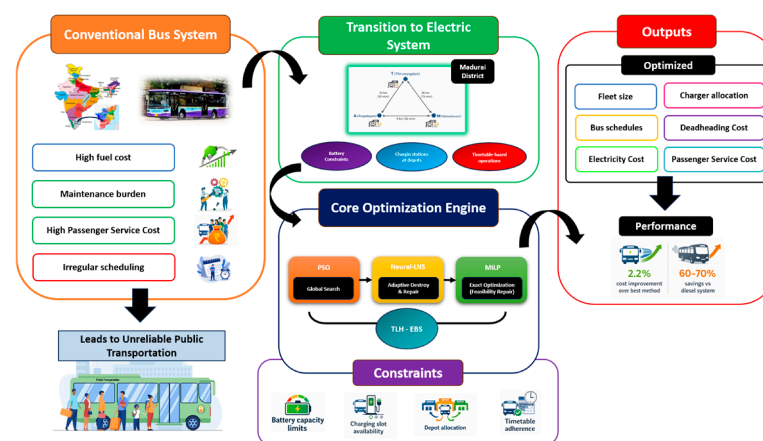
Furthermore, several existing works do not explicitly incorporate charger allocation planning, deadheading minimization, or multi-level decision structures. In contrast, the proposed Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework integrates fleet scheduling, charging infrastructure allocation, and energy feasibility constraints within a unified optimization structure. By combining metaheuristic exploration with exact repair mechanisms, the framework efficiently handles large-scale scheduling problems while maintaining strict timetable adherence and energy feasibility. The overview of the proposed framework is shown in Figure 2.

Additionally, the proposed model has been validated using a real-world transit network case study by demonstrating its practical applicability for district-level electric bus operations. These features collectively distinguish the TLH-EBS framework from the existing methods and highlight its potential for supporting cost-efficient and scalable electric bus scheduling.

Table 1. Comparison of representative electric bus scheduling algorithms with the proposed TLH-EBS framework.

Study	Optimization Approach Used in Study	A	B	C	D	E	F	G	H
[1]	MILP	✓	✗	✓	✗	✗	✗	✗	✗
[2]	MILP	✓	✓	✓	✗	✗	✗	✗	✗
[3]	Genetic Algorithm	✓	✗	✓	✓	✓	✗	✓	✗
[4]	Hybrid Heuristic	✓	✓	✓	✓	✓	✗	✓	✗
[5]	Multi-objective Optimization	✓	✓	✓	✗	✗	✗	✗	✗
[7]	Large Neighborhood Search	✓	✗	✓	✓	✓	✗	✓	✗
[12]	Mathematical Programming	✓	✓	✓	✗	✗	✗	✗	✗
[18]	Robust Optimization	✓	✗	✓	✗	✗	✗	✗	✗
[21]	Stochastic Optimization	✓	✓	✓	✗	✗	✗	✗	✗
[28]	Model Predictive Control	✓	✗	✓	✗	✗	✓	✓	✗
TLH-EBS	Tri-Level Hybrid Optimization	✓	✓	✓	✓	✓	✓	✓	✓

Timetable-Based Trip Scheduling (A), Charger Allocation (B), Battery Energy Constraint (C), Deadheading Consideration (D), Hybrid Optimization (E), Multi-Level Decision (F), Large-Scale Network Capability (G), and Real Transit Case Study (H).

**Figure 2.** Overview of the proposed framework.

1.1. Current Trend in India

India is currently the most populous country in the world, with a population exceeding 1.47 billion, representing approximately 17.8% of the global population, and this rapid population growth has significantly increased transportation demand, vehicle ownership, and dependence on mobility systems across the country. Over the past decade, India has experienced a major increase in vehicle registrations, with the total number of registered vehicles increasing from approximately 190 million in 2014 to over 350 million by 2022–2024, indicating a significant shift toward private and intermediate transportation modes due to urbanization, economic development, and improved road infrastructure. Population distribution across India shows strong regional variation, with North India holding nearly 50% of India's population, while the five major South Indian states (Tamil Nadu, Kerala, Karnataka, Andhra Pradesh, and Telangana) together account for approximately 20% of the population. As of 2024–2025, North India remains significantly more populous, dominated by Uttar Pradesh (~241 million) and Bihar (~131 million), followed by Madhya Pradesh (~89 million), Rajasthan (~82 million), and West Bengal (~100 million), whereas major South

Indian states include Tamil Nadu (~76–77 million), Karnataka (~67–68 million), Andhra Pradesh (~53 million), Telangana (~38 million), and Kerala (~35–36 million), as shown in Figure 3. Northern states generally have higher fertility rates and younger populations, while southern states have lower growth rates and aging populations, which directly influence transportation demand patterns and vehicle ownership behavior. When transportation modes are categorized into four-wheelers, three-wheelers, and public buses, regional differences become evident, where four-wheeler usage in North India is approximately 12–14% and in South India, approximately 15–18%, while three-wheeler usage in North India is approximately 4–6% and in South India approximately 3–5%, and bus usage is less than 1% in North India and approximately 1.2–1.5% in South India, indicating that South India relies more on organized public transport systems whereas North India relies more on intermediate transport modes such as auto-rickshaws and private vehicles, as shown in Figure 4.



Figure 3. Comparative analysis of population distribution across major North and South Indian States.

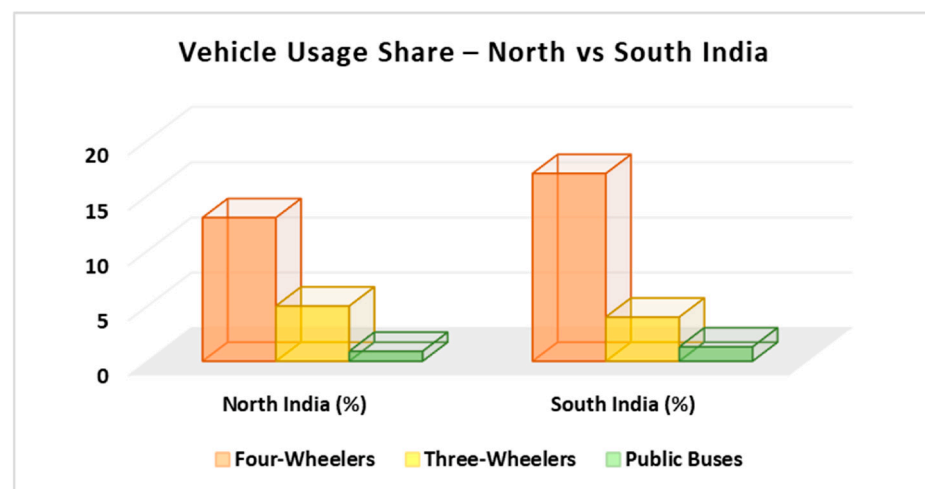


Figure 4. Comparative distribution of vehicle usage modes across North and South India.

In terms of vehicle ownership trends, states such as Kerala possess approximately 2.89 million registered cars, nearly matching Uttar Pradesh with approximately 2.79 million

registered cars, despite the significant population difference, indicating higher vehicle penetration in South India. In contrast, a state such as Bihar has some of the lowest car ownership levels, with fewer than 35 cars per 1000 people. As of 2024–2025, North India remains significantly more populous, dominated by Uttar Pradesh (~241 million) and Bihar (~131 million), followed by Madhya Pradesh (~89 million), Rajasthan (~82 million), and West Bengal (~100 million), whereas major South Indian states include Tamil Nadu (~76–77 million), Karnataka (~67–68 million), Andhra Pradesh (~53 million), Telangana (~38 million), and Kerala (~35–36 million).

Figures 5 and 6 show Economic Class-wise Vehicle Usage Distribution in major North Indian States and South Indian States. In the three-wheeler segment, Uttar Pradesh has become a national leader, accounting for approximately 38% of all new electric three-wheeler registrations, while in South India, three-wheelers are more frequently used for last-mile connectivity and logistics operations. Over the last decade, the modal share in many cities has shifted away from public buses and toward private four-wheelers, with public bus usage declining by nearly 40% in some cities, indicating increasing dependence on private and rental transportation.

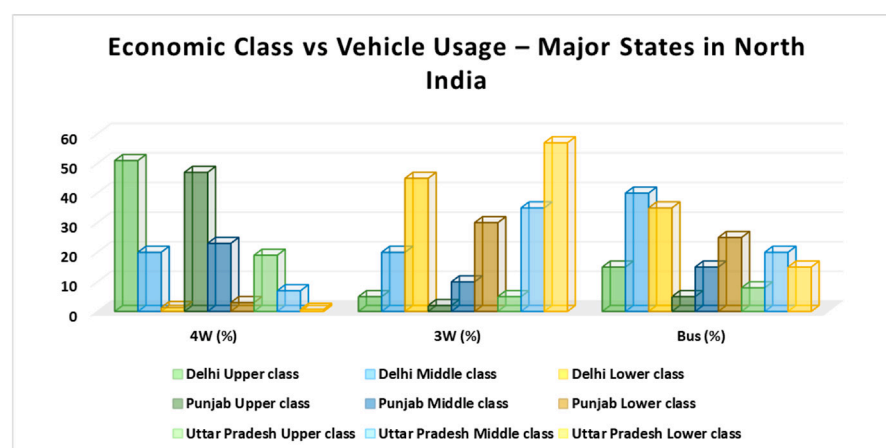


Figure 5. Economic Class-wise Vehicle Usage Distribution in major North Indian States.

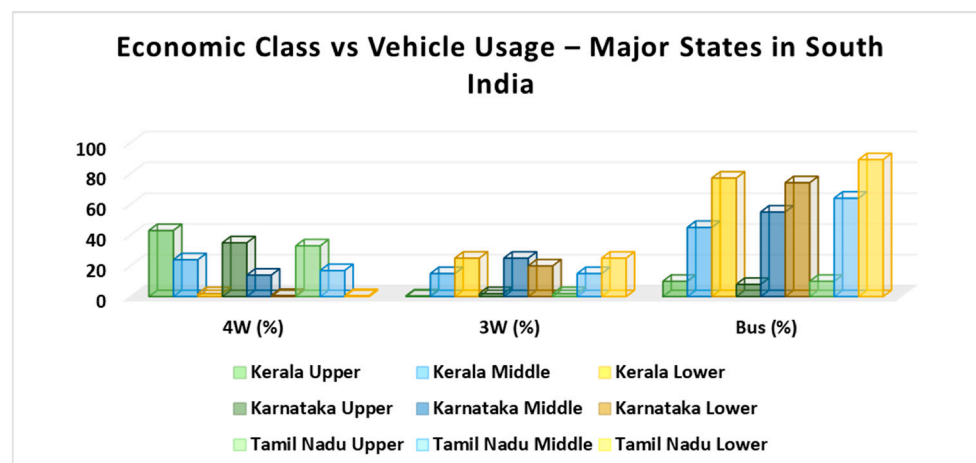


Figure 6. Economic Class-wise Vehicle Usage Distribution in major South Indian States.

Transportation usage is also strongly influenced by economic class. In North India, vehicle usage is highly polarized, where upper-class populations in states such as Delhi and Punjab show private car usage of approximately 45–52%, while middle-class populations rely on a combination of autos and buses, and lower-income populations rely heavily on three-wheelers and buses. In contrast, South India shows a much higher dependency on

public transport systems across all economic classes, due to well-managed State Transport Corporations. For example, in Tamil Nadu, upper-class four-wheeler usage is approximately 28–35%, middle-class four-wheeler usage is 12–18%, and lower-class usage is less than 1%, while public bus usage among the lower-income groups reaches approximately 85–90%, indicating strong dependence on public transportation systems. Tamil Nadu has one of the largest public transportation systems in India, carrying approximately 1.76 crore passengers daily, and along with Karnataka, it operates approximately 26,054 buses carrying around 1 crore passengers daily. Tamil Nadu operates approximately 20,260 buses, making South India the national leader in public mobility compared to northern states such as Delhi and Uttar Pradesh.

In addition to transportation infrastructure development, Tamil Nadu has implemented social mobility initiatives such as the free bus travel scheme for women, known as Vidiyal Payanam, launched in May 2021, which provides free travel for women, transgender persons, and differently abled persons in ordinary-fare state-owned buses, thereby increasing public transportation usage and reducing household transportation expenditure. Alongside social mobility initiatives, Tamil Nadu has also initiated an accelerated transition toward electric public transportation under the FAME II scheme and the Tamil Nadu Electric Vehicle Policy 2023, with a target of electrifying approximately 30% of the State Transport Undertaking bus fleet by 2030 to reduce diesel dependency, mitigate urban air pollution, and stabilize long-term operational expenditure. Under the FAME II scheme, electric buses receive incentives of approximately INR 20,000 per kWh of battery capacity, while the Tamil Nadu EV Policy provided subsidies of up to INR 1 million per bus and 100% electricity tax exemption for charging stations until December 2025. Tamil Nadu follows a Gross Cost Contract (GCC) model, where private operators own and maintain electric buses while the government pays a fixed cost per kilometer, making efficient scheduling and fleet utilization extremely important for economic viability.

The transportation usage pattern in Madurai district shows a clear variation based on economic class, indicating significant differences in vehicle ownership and public transport dependency.

Among the upper-class population, private four-wheelers are the dominant mode of transportation, with approximately 22–26% of upper-income households using private cars for daily travel, while only around 3% use shared autos, and about 5% depend on public buses. In contrast, the middle-class population shows a mixed transportation pattern, where private car usage is relatively lower at approximately 8–14%, while shared auto usage increases significantly to around 30–35%, and public bus usage becomes the primary mode of transportation, accounting for approximately 55–65% of middle-class commuters. The lower-income population shows very high dependency on public transportation and intermediate transport modes, where private car usage is negligible at less than 1%, shared auto usage is approximately 40–45%, and public bus usage reaches approximately 75–85%, indicating strong reliance on affordable public transportation systems for daily commuting, as shown in Figure 7. These observations clearly demonstrate that public bus transportation plays a critical role in the mobility of middle- and lower-income populations, while private vehicles are predominantly used by upper-income groups. The high share of auto usage among middle- and lower-income populations also indicates last-mile connectivity dependency, which further emphasizes the need for efficient public transport scheduling and route planning to reduce the reliance on intermediate rental transportation and improve overall transportation efficiency in the Madurai district.

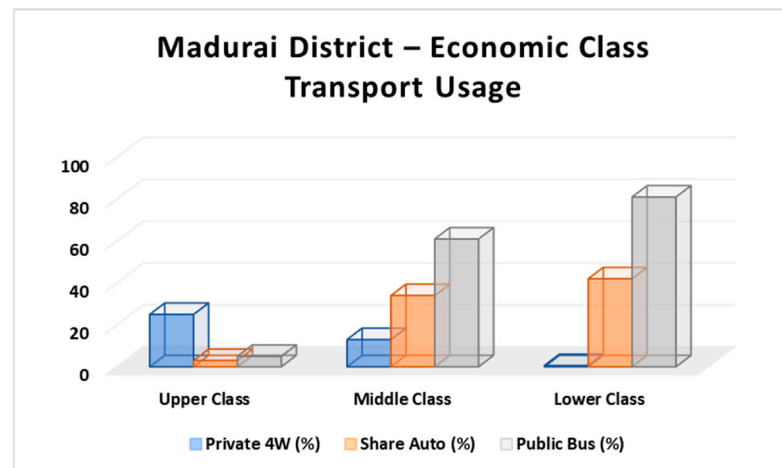


Figure 7. Socio-economic distribution of transport mode usage in Madurai district.

When focusing specifically on Madurai district, which has an estimated population of 36.70 lakh, transportation usage is distributed across different vehicle categories, where public buses serve approximately 25.6–29.3 lakh people (70–80% of the population), three-wheelers serve approximately 4.7–5.5 lakh people (13–15%), private four-wheelers serve approximately 2.9–4.4 lakh people (8–12%), rental app-based autos and bikes are used by approximately 5.5–7.3 lakh people (15–20%), and rental app-based cabs are used by approximately 1.1–1.8 lakh people (3–5%), indicating that a significant portion of the population still relies on rental transportation, even though public transportation is widely available, as shown in Figure 8. This increasing usage of rental vehicles leads to higher transportation expenses, increased traffic congestion, and inefficient utilization of public transportation infrastructure. Therefore, there is a need to analyze transportation usage patterns and evaluate the economic benefits that people can obtain by shifting from rental transportation options to public transportation systems while simultaneously supporting electric bus deployment. To achieve this effectively, proper scheduling, fleet planning, charging coordination, and efficient management of public transportation systems are necessary, and in this context, the development of an integrated fleet-charger-schedule optimization framework, such as the proposed TLH-EBS framework, becomes critical to enable cost-efficient electrification and sustainable public transportation operation under strict service constraints.

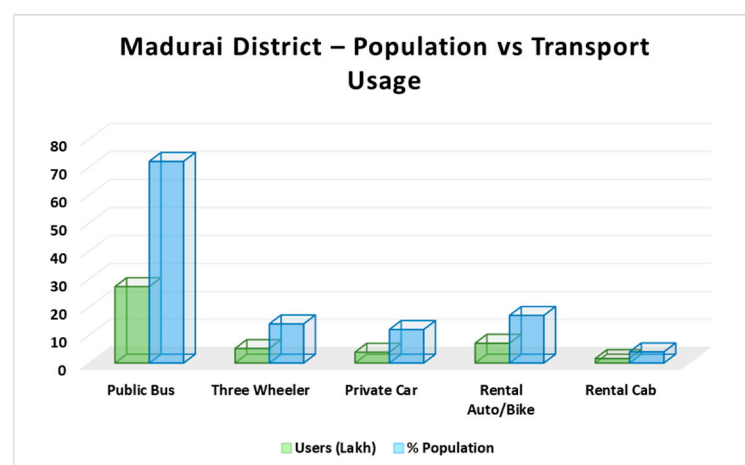


Figure 8. Relationship between population distribution and transport mode usage in Madurai district.

1.2. Research Gap

Despite the growing body of research on electric bus scheduling, several important gaps remain in the existing literature:

1. Fragmented optimization focus: Most previous studies address individual aspects such as fleet scheduling, charging coordination, or charger infrastructure planning separately, rather than optimizing them simultaneously.
2. Limited scalability of solution methods: Many models rely on single optimization techniques (e.g., MILP or heuristic algorithms), which often face computational challenges when applied to large transit networks with strict timetable constraints.
3. Simplified representation of electric bus operations: Several existing models assume homogeneous vehicle fleets or simplified charging behaviors, which may not accurately capture real-world variations in battery capacity, energy consumption, and charging requirements.
4. Lack of real-world validation: Many studies have been evaluated using synthetic datasets or simplified networks, which may not fully represent the operational complexity of district-level public transport systems.

These limitations highlight the need for an integrated and scalable optimization framework that jointly considers fleet composition, charger allocation, and operational scheduling while ensuring energy feasibility under realistic transit conditions.

1.3. Contributions of This Study

To address the identified research gaps, this study proposes a Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework for cost-aware electric bus operations. The proposed approach integrates multiple optimization strategies to efficiently solve large-scale scheduling problems under practical operational constraints. The main contributions of this study are summarized as follows:

1. Development of a hierarchical Tri-Level hybrid scheduling framework integrating Particle Swarm Optimization (PSO), Rule-Based Scoring Large Neighborhood Search (RBS-LNS), and Mixed-Integer Linear Programming (MILP) repair mechanisms.
2. Simultaneous optimization of fleet size and charger allocation while satisfying strict timetable adherence constraints in electric bus transit operations.
3. Explicit modeling of heterogeneous electric bus characteristics, including battery capacity, energy consumption, and charging feasibility constraints.
4. Real-world implementation on district-level public transport corridors, demonstrating the applicability of the proposed framework for practical transit systems.
5. Comprehensive performance comparison against the conventional optimization approaches and equivalent diesel-based operations, highlighting the economic and operational advantages of the proposed scheduling framework.

Unlike the conventional studies that apply a single optimization paradigm, the proposed framework integrates strategic charger allocation, tactical schedule restructuring, and operational repair optimization within a unified scheduling environment. The novelty of the proposed approach does not lie in the individual algorithms themselves, but in their coordinated application to a large-scale electric bus scheduling problem involving simultaneous fleet sizing, charger allocation, charging coordination, and timetable-constrained trip assignment. This integration enables efficient handling of highly coupled operational decisions that are difficult to address by using standalone optimization methods.

2. Problem Description

The problem addresses the optimal scheduling of electric buses within a district-level public transport network operating under a strictly predefined timetable, where each trip must depart exactly at its scheduled time without any delay. Unlike conventional diesel systems, electric buses are constrained by limited battery capacity and the need for periodic recharging at depots equipped with a finite number of chargers. During operations, each bus performs a sequence of trips while consuming energy proportional to travel distance, and whenever the state-of-charge becomes insufficient, it must be routed to the nearest depot for full recharging, potentially incurring waiting time due to charger unavailability. This scheduling environment involves a tightly coupled interaction among fleet size, charging infrastructure, and trip assignment decisions, where inefficiencies in one component directly affect the others. The objective is to minimize the total annual system cost, which includes capital investments for buses and chargers, electricity consumption, deadheading movements, and passenger service operations, while strictly satisfying operational constraints such as exact timetable adherence, battery feasibility, minimum layover requirements, charger capacity limits, and depot parking restrictions. As a result, the problem evolves into a complex integrated optimization challenge, where fleet availability influences charging demand, charging congestion affects schedule feasibility, and any disruption may require deploying additional buses to maintain service reliability. To effectively address this complexity, the study proposes a Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework, which integrates multiple optimization strategies to jointly optimize fleet size, charging infrastructure allocation, and daily bus scheduling under strict operational constraints.

3. System Description

3.1. Study Area and Network Configuration

The proposed Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework has been implemented in a district-level public transport network in Madurai, Tamil Nadu, comprising three major interconnected terminals: Thirumangalam (T), Arapalayam (A), and Mattuthavani (M).

These terminals form a triangular bidirectional corridor structure that represents a realistic operational setting for district transport services, as shown in Figure 9. The Thirumangalam–Arapalayam corridor spans 22 km with an average travel duration of 50 min; the Arapalayam–Mattuthavani corridor covers 9 km with a travel time of approximately 30 min, and the Mattuthavani–Thirumangalam route extends 28 km, requiring 75 min of travel. These durations incorporate typical traffic conditions. The system operates daily from 05:00 AM to 12:30 AM, and a mandatory layover time of 10 min is imposed at every terminal to accommodate passenger boarding and alighting before the commencement of the subsequent trip. The network configuration creates a cyclic operational structure in which buses continuously circulate among the three corridors while satisfying strict timetable requirements.

3.2. Depot Infrastructure and Charging Configuration

The operational network is supported by three depots equipped with charging facilities. The Thirumangalam depot is located 2 km from the Thirumangalam bus stand, requiring approximately 6 min of deadheading travel. The Ponmeni depot serves the Arapalayam stand and is situated 5 km away, corresponding to a 12 min travel time. The Mattuthavani depot is positioned 1 km from the Mattuthavani bus stand, requiring 5 min of travel. All charging operations are performed exclusively at these depots. Whenever a bus requires charging, it must travel from the bus stand to its nearest depot, undergo a

complete charging cycle, and return to the stand before resuming service. If a charging slot is unavailable upon arrival, the bus must wait until a charger becomes free, and this waiting duration is explicitly incorporated into scheduling feasibility. Deadheading trips between the depot and the stand are accounted for in both energy consumption and cost calculations. The depots also have limited parking capacities, accommodating 30 buses at Thirumangalam, 20 buses at Ponmeni, and 70 buses at Mattuthavani. If the number of operational buses exceeds depot parking capacity, surplus buses remain stationed at the bus stand overnight. However, all buses are assumed to start each operational day with a full battery charge to ensure consistency in daily scheduling.

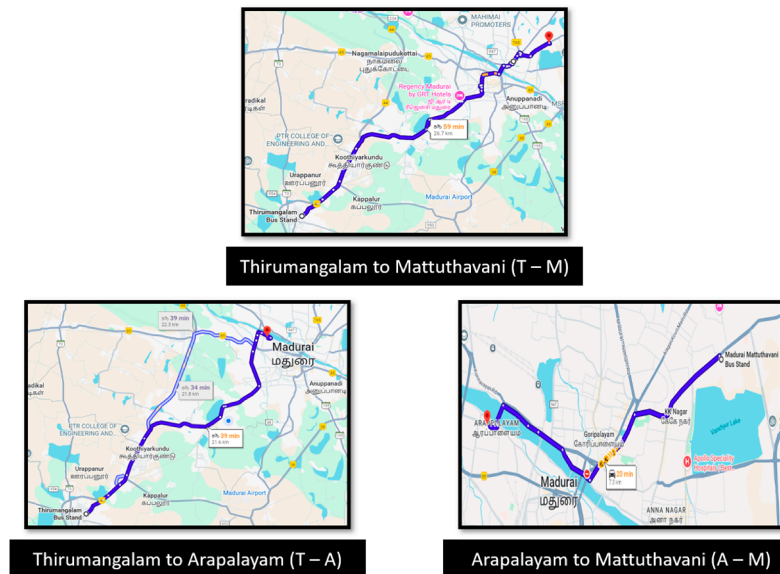


Figure 9. Study area route network connecting Thirumangalam, Arapalayam, and Mattuthavani.

3.3. Electric Bus Fleet Characteristics

The system considers two heterogeneous electric bus types with distinct energy and charging characteristics, as shown in Figure 10. The first type is a 12 m air-conditioned electric bus with a usable battery capacity of 360 kWh, consuming 2.0 kWh per kilometer during passenger service and 1.2 kWh per kilometer during deadheading. This vehicle supports 240 kW fast charging, and its purchase cost is 60 Lakhs (USD 63,332.88). The second type is a 9 m non-air-conditioned electric bus with a usable battery capacity of 194 kWh, consuming 1.4 kWh per kilometer during passenger operation and 1.0 kWh per kilometer during deadheading. It supports 120 kW charging and has a purchase cost of INR 45 lakhs (USD 47,150). The project lifetime is assumed to be 12 years, and the capital costs are annualized using an interest rate of 9 percent. The electricity tariff is fixed at INR 8.10 (USD 0.08491) per kWh. Differences in battery capacity, energy consumption rate, and charging power introduce heterogeneity into the scheduling problem, requiring energy-aware decision-making for trip assignment and charging coordination.

3.4. Timetable Structure and Service Frequency

The timetable follows strict headway-based service constraints reflecting real-world public transport practice, as shown in Figure 11. During peak hours, defined as 07:30 AM–09:30 AM and 4:30 PM–8:30 PM, buses of each type must depart every 10 min from each terminal.



Figure 10. Electric bus fleet characteristics of Type-1 and Type-2.

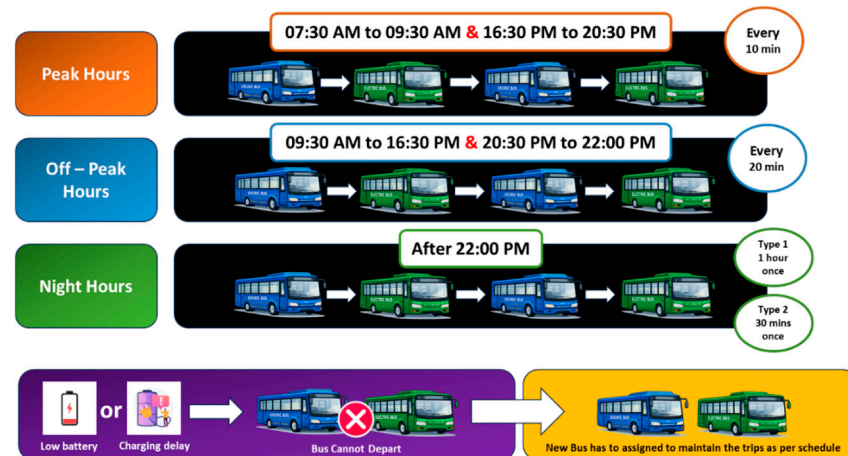


Figure 11. Timetable structure for peak and off-peak operations.

During off-peak periods, departures occur every 20 min for each type. After 10:00 PM, service frequency is reduced, with Type-1 buses departing at hourly intervals beginning at 10:00 PM and Type-2 buses departing at hourly intervals beginning at 10:30 PM. No penalty-based relaxation is allowed in the model; therefore, buses must depart exactly at their scheduled departure time. If an assigned bus cannot depart due to insufficient state-of-charge or charging delays, an additional bus must be deployed to maintain schedule integrity. This strict timetable adherence significantly increases the complexity of the scheduling problem compared to the conventional diesel operations. The optimized timetable operates from 05:00 AM to 00:30 AM and consists of six directional corridor movements connecting the three terminals of the Madurai district transit network, namely Arapalayam–Mattuthavani (A–M), Mattuthavani–Arapalayam (M–A), Arapalayam–Thirumangalam (A–T), Thirumangalam–Arapalayam (T–A), Mattuthavani–Thirumangalam (M–T), and Thirumangalam–Mattuthavani (T–M). The operating day is divided into multiple service periods comprising an early morning off-peak period (05:00 AM–07:00 AM), morning peak period (07:00 AM–10:00 AM), midday off-peak period (10:00 AM–5:00 PM), evening peak period (5:00 PM–8:00 PM), late evening off-peak period (8:00 PM–10:00 PM), and a night operating period (10:00 PM–00:30 AM) with reduced service frequency.

Across the entire network, peak-period operations contribute 396 scheduled passenger trips (48.9%), off-peak operations contribute 384 trips (47.4%), and night services account for the remaining 30 trips (3.7%), resulting in a total of 810 scheduled passenger trips per operating day. Furthermore, Type-1 buses contribute 414 trips (51.1%), while Type-2 buses contribute 396 trips (48.9%). The slight imbalance between the two vehicle categories arises from the staggered dispatch strategy adopted to maintain uniform passenger service intervals while simultaneously improving charging flexibility and reducing charger congestion. Consequently, the reported 810 daily trips emerge from the combined effects of corridor-

level dispatch frequencies, directional operations, bus-type allocation, and time-dependent service schedules rather than from headway values alone.

3.5. Operational and Energy Constraints

Each bus must satisfy an energy feasibility condition before initiating a scheduled trip. The available state-of-charge must be sufficient to complete the passenger trip, travel to the nearest depot afterward, and maintain a predefined reserve margin. If this condition is not satisfied, the bus must first deadhead to the depot for charging. Charging is modeled as a full-cycle operation rather than partial charging, ensuring operational predictability and simplifying daily energy planning. Charging slot availability is explicitly enforced; buses arriving at a depot may experience waiting time if chargers are occupied. Deadheading trips are included in both energy and cost calculations, reflecting realistic operational behavior. The combination of strict timetable enforcement, heterogeneous fleet characteristics, charging coordination, and depot capacity limits creates a tightly constrained scheduling environment.

The present study adopts a depot-based full-cycle charging strategy, whereby electric buses are recharged to their full usable battery capacity whenever charging is initiated. This assumption is consistent with the current charging practices adopted by many state transport undertakings in India, where depot charging represents the dominant operational model. Incorporating partial charging would require simultaneous optimization of charging duration, charging quantity, charger occupancy, and battery cycling behavior, thereby significantly increasing the complexity of the scheduling problem. Consequently, full-cycle charging is adopted as a baseline operational strategy to enable systematic evaluation of fleet scheduling and charger allocation decisions. Future research can extend the proposed framework by incorporating opportunity charging and partial charging strategies under dynamic operational conditions. Furthermore, strict timetable adherence is enforced throughout the scheduling process. Whenever a scheduled departure cannot be satisfied due to insufficient state-of-charge or charging delays, an additional electric bus is introduced into the system. This assumption reflects practical operating policies followed by public transport corporations, where departure cancellations are generally not permitted, and service reliability must be maintained. Therefore, reserve vehicle deployment is considered a realistic mechanism for preserving timetable integrity under operational constraints.

4. Mathematical Formulation

4.1. Modeling Framework and Notation

The electric bus scheduling problem is formulated as an integrated fleet sizing, charger allocation, and operational assignment optimization model. The formulation explicitly captures the temporal structure of the timetable, heterogeneous fleet characteristics, energy feasibility conditions, and depot-level charging coordination. Let D denote the set of depots, S the set of bus terminals (stands), $B = \{1, 2\}$ the set of electric bus types, and T the set of scheduled trips within the planning horizon. Each trip $t \in T$ is characterized by origin stand o_t , destination stand d_t , scheduled departure time τ_t^{dep} , arrival time τ_t^{arr} , and passenger distance L_t . Let L_{sd} represent the deadheading distance between stand s and its nearest depot. For each bus type $b \in B$, let E_b^{max} denote usable battery capacity, α_b energy consumption per kilometer during passenger service, β_b energy consumption per kilometer during deadheading, P_b purchase cost, and P_{cb} charger investment cost. The electricity tariff is denoted by λ , the annual interest rate by i , and the project lifetime by n .

Decision variables include the number of buses of each type N_b , the number of chargers of type b installed at depot d , denoted C_{db} , and the assignment of buses to trips. Let a

binary variable x_{it} equal to 1, if bus i serves trip t , and 0 otherwise. The state-of-charge of bus i immediately before the departure of the trip t is denoted as SOC_{it} . The objective is to minimize total annual scheduling cost while ensuring strict timetable adherence, energy feasibility, charging availability, and depot capacity compliance.

4.2. Objective Function

The total annual cost is expressed as

$$M = M_1 + M_2 + M_3 + M_4 + M_5 \quad (1)$$

where each term corresponds to a major economic component of the system.

4.2.1. Annualized Bus Capital Cost

Capital recovery is computed using the following annuity factor:

$$A = \frac{i(1+i)^n}{(1+i)^n - 1} \quad (2)$$

The annualized fleet investment becomes

$$M_1 = A \sum_{b \in B} N_b P_b \quad (3)$$

This term links long-term capital investment with operational scheduling, since fleet size directly influences the ability to meet strict headway requirements.

4.2.2. Annualized Charger Investment Cost

Charging infrastructure is similarly annualized:

$$M_2 = A \sum_{d \in D} \sum_{b \in B} C_{db} P_{cb} \quad (4)$$

This component couples the infrastructure decisions with operational feasibility, as insufficient chargers increase waiting time and, potentially, require additional buses.

4.2.3. Electricity Consumption Cost

Daily energy consumption of the bus i is determined by summing energy used for passenger trips, deadheading movements, and overnight recharging.

Energy for a passenger trip t served by bus type b :

$$E_{it}^{load} = \alpha_b L_t \quad (5)$$

Energy for deadheading from stand to depot:

$$E_{it}^{dead} = \beta_b L_{sd} \quad (6)$$

The daily energy consumption of the bus i becomes

$$E_i^{daily} = \sum_{t \in T} x_{it} \alpha_b L_t + \sum_{k \in DH_i} \beta_b L_k \quad (7)$$

where DH_i represents the set of deadheading movements of the bus i .

The annual electricity cost is therefore

$$M_3 = 365\lambda \sum_i E_i^{daily} \quad (8)$$

This component explicitly captures heterogeneous energy rates across bus types.

4.2.4. Deadheading Operational Cost

Deadheading incurs additional operational costs due to driver wages, tire wear, and auxiliary energy losses. Let c_b^{dead} denote per-kilometer deadheading cost. The annual deadheading cost is

$$M_4 = 365 \sum_i \sum_{k \in DH_i} c_b^{dead} L_k \quad (9)$$

Deadheading is explicitly modeled because charging is depot-based rather than opportunity-based.

4.2.5. Passenger Service Cost

Passenger service cost reflects operational expenditure during loaded trips. Let c_b^{load} denote per-kilometer service cost. Then

$$M_5 = 365 \sum_i \sum_{t \in T} x_{it} c_b^{load} L_t \quad (10)$$

4.3. State-of-Charge Dynamics

The SOC evolution of each bus is temporally dependent. For bus i serving trip t :

$$SOC_{i,t}^{after} = SOC_{it} - \alpha_b L_t \quad (11)$$

If the bus deadheads to the depot:

$$SOC_{i,t}^{after} = SOC_{i,t}^{after} - \beta_b L_{sd} \quad (12)$$

Charging is modeled as full-cycle recovery:

$$SOC_i^{after\ charge} = E_b^{max} \quad (13)$$

This discrete SOC reset simplifies operational predictability and reflects practical depot charging policies.

4.4. Energy Feasibility Constraint

Before initiating the trip t , energy sufficiency must hold:

$$SOC_{it} \geq \alpha_b L_t + \beta_b L_{sd} + SOC_b^{reserve} \quad (14)$$

This ensures that the bus can complete the passenger trip, travel to the depot afterward, and maintain a safety reserve.

4.5. Temporal Feasibility Constraint

If bus i serves two consecutive trips t and t' :

$$\tau_t^{arr} + \Delta \leq \tau_{t'}^{dep} \quad (15)$$

where Δ is the minimum layover time (10 min). This constraint enforces timetable continuity.

4.6. Charging Capacity Constraint

At depot d , at any time interval θ :

$$\sum_{i \in \text{charging}(d, \theta)} 1 \leq C_{db} \quad (16)$$

If violated, a waiting time is introduced, affecting subsequent departures.

4.7. Depot Parking Constraint

At the end of the operational day:

$$\sum_{i \in \text{depot } d} 1 \leq \text{Cap}_d \quad (17)$$

If they exceed, buses remain at the stand overnight.

4.8. Strict Timetable Enforcement

For each scheduled departure t :

$$\exists i \text{ such that } x_{it} = 1 \text{ and actual departure} = \tau_t^{\text{dep}} \quad (18)$$

No slack or penalty relaxation is allowed. If infeasible, additional fleet must be introduced.

4.9. Problem Characteristics

The formulated model represents a highly coupled mixed-integer nonlinear scheduling problem. Fleet size decisions influence charging congestion, charging congestion affects waiting time, waiting time impacts timetable feasibility, and timetable feasibility determines required fleet size. This circular dependency makes the problem computationally complex and unsuitable for standalone exact optimization at a realistic scale. Therefore, a hierarchical hybrid solution strategy is developed to decompose global exploration, adaptive neighborhood restructuring, and exact combinatorial repair for forming the foundation of the TLH-EBS framework. The mathematical formulation presented in this study focuses on the principal decision variables, objective functions, and operational constraints governing the integrated scheduling problem. The actual implementation of the TLH-EBS framework is carried out through an event-based simulation mechanism that explicitly tracks trip departures, layovers, charging activities, charger waiting times, deadheading movements, and state-of-charge evolution of every vehicle throughout the operating day. This modeling approach has been adopted to improve computational tractability for the large-scale case study while preserving operational realism. However, several operational interactions, including charger waiting, charging duration, reserve-bus deployment, and event-based vehicle movements, are implemented through an event-driven simulation layer embedded within the TLH-EBS framework rather than through a fully time-indexed mathematical formulation. The event-driven simulation explicitly updates each bus state across sequential operational events, including passenger-service trips, terminal layovers, deadheading movements, depot charging, charger waiting, and battery state-of-charge evolution throughout the operating day.

5. Optimization Algorithms and Proposed TLH-EBS Framework

The overall structure of the proposed TLH-EBS framework is illustrated in Figure 12, where strategic, tactical, and operational decision layers are hierarchically integrated.

5.1. Standalone MILP Approach

In the standalone MILP setting, the core scheduling objective is to assign all scheduled trips to a minimum number of buses while satisfying strict temporal feasibility. Let T be the set of trips and let $K = \{1, \dots, K_{\max}\}$ be a sufficiently large index set of candidate buses. Define a binary assignment variable x_{tk} that equals 1, if trip t is served by a bus k , and 0 otherwise, and a bus activation variable u_k that equals 1, if bus k is used.

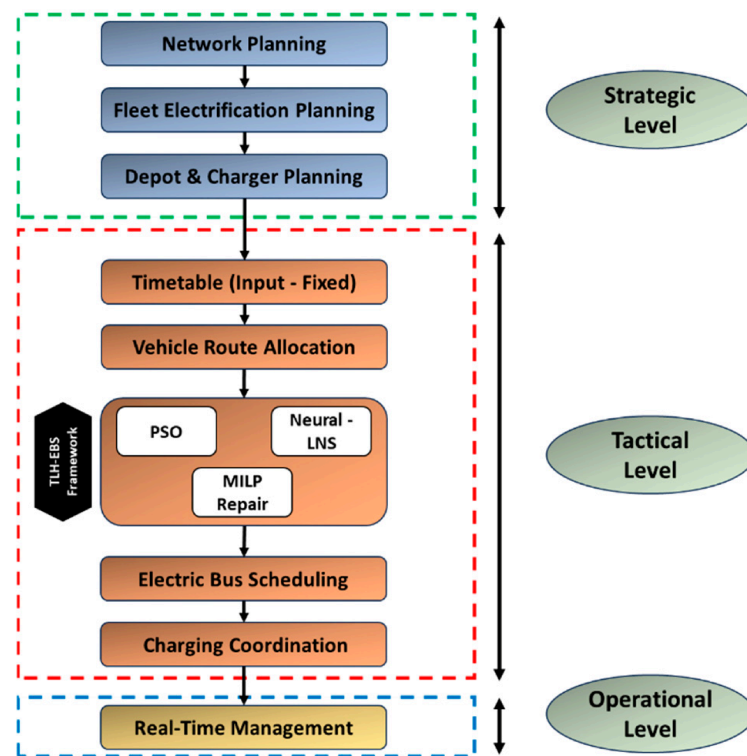


Figure 12. Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework.

The MILP minimizes the number of active buses:

$$\min \sum_{k \in K} u_k \quad (19)$$

Each trip must be assigned exactly once:

$$\sum_{k \in K} x_{tk} = 1 \forall t \in T \quad (20)$$

Assignment implies activation:

$$x_{tk} \leq u_k \forall t \in T, \forall k \in K \quad (21)$$

Let the scheduled departure and arrival times of the trip t be τ_t^{dep} and τ_t^{arr} . Let Δ be the mandatory layover time (10 min). Two trips t and t' are incompatible for the same bus if they overlap in time (including layover). Define a compatibility indicator:

$$\chi_{tt'} = \begin{cases} 1, & \text{if } \tau_t^{arr} + \Delta \leq \tau_{t'}^{dep} \text{ or } \tau_{t'}^{arr} + \Delta \leq \tau_t^{dep} \\ 0, & \text{otherwise} \end{cases} \quad (22)$$

Then, non-overlap can be enforced by

$$x_{tk} + x_{t'k} \leq 1 \forall k \in K, \forall (t, t') : \chi_{tt'} = 0 \quad (23)$$

This MILP is exact for time-feasible packing. However, full EB scheduling also requires SOC feasibility, depot charging, charger waiting, and depot-only charging, which introduce nonlinearities and time-dependent resource constraints. Therefore, MILP is scalable only when restricted to partial horizons or repair subproblems, as shown in Algorithm 1.

Algorithm 1 Standalone MILP Approach

```

1: Input route, depot, bus, charger, and timetable data
2: Generate all scheduled trips
3: Initialize baseline charging policy and charger allocation
4: Apply MILP packing for early-horizon trips
5: Assign non-overlapping trips to the minimum number of buses
6: Simulate daily bus movement
7: Check SOC feasibility for trip and nearest depot reachability
8: if feasible then
9:     Operate loaded trip
10: else
11:     Send bus to the nearest depot
12:     Wait if charger slot is unavailable
13:     Perform full charging
14:     Return bus to bus stand
15: end if
16: Apply layover and continue next trip
17: Update deadheading, charging, and trip events
18: Compute fleet size, trip count, deadheading trips, and annual cost
19: Return MILP schedule

```

5.2. Standalone Particle Swarm Optimization (PSO)

Standalone PSO is used to optimize macro-level system decisions without requiring explicit gradients. Each particle represents a decision vector containing charging policy parameters and depot-wise charger allocations, as shown in Algorithm 2. Let the particle position be at the iteration k be x_p^k and velocity be v_p^k . In the present case, a particle encodes

$$x_p = [\phi_r, \phi_c, C_{DT,1}, C_{DA,1}, C_{DM,1}, C_{DT,2}, C_{DA,2}, C_{DM,2}] \quad (24)$$

where ϕ_r is the reserve SOC fraction and ϕ_c is the charging trigger fraction. Since chargers are integers, decoding uses rounding:

$$\hat{C}_{db} = \max\{0, \text{round}(C_{db})\} \quad (25)$$

The PSO update equations are

$$v_p^{k+1} = \omega v_p^k + c_1 r_1 (\text{pbest}_p - x_p^k) + c_2 r_2 (\text{gbest} - x_p^k) \quad (26)$$

$$x_p^{k+1} = x_p^k + v_p^{k+1} \quad (27)$$

For each particle, a strict simulation produces an annual cost:

$$M(x_p) = M_1(x_p) + M_2(x_p) + M_3(x_p) + M_4(x_p) + M_5(x_p) \quad (28)$$

With feasibility enforced through strict timetable rules (if a bus cannot depart exactly at τ_t^{dep} , a new bus is created), PSO is effective for exploring charger-policy combinations, but it does not explicitly perform deep combinatorial restructuring of trip chains; it mostly improves solutions through parameter search, which may stagnate.

Algorithm 2 Standalone Particle Swarm Optimization (PSO)

- 1: Input route, depot, bus, charger, and timetable data
- 2: Generate all scheduled trips
- 3: Initialize swarm particles
- 4: Decode each particle into scheduling policy and charger allocation
- 5: Simulate daily electric bus operation
- 6: Check strict timetable and SOC feasibility
- 7: **if** trip is infeasible, then
- 8: Send bus to nearest depot for charging
- 9: **end if**
- 10: Operate feasible trips and record events
- 11: Compute annual total scheduling cost
- 12: Update personal best and global best
- 13: Update particle velocity and position
- 14: Repeat until the stopping criterion is reached
- 15: **Return** the best PSO schedule

5.3. Standalone Rule-Based Scoring Large Neighborhood Search (RBS-LNS)

Standalone RBS-LNS is a destroy-and-repair heuristic that improves a schedule by selectively removing (“destroying”) inefficient parts and reinserting them, as shown in Algorithm 3. Let the current schedule be $\mathcal{S}$ with a bus set $\mathcal{B}$. For each bus $i \in \mathcal{B}$, operational features are computed.

Algorithm 3 Standalone Rule-Based Scoring Large Neighborhood Search (RBS-LNS)

- 1: Input route, depot, bus, charger, and timetable data
- 2: Generate all scheduled trips
- 3: Create initial solution using reduced PSO
- 4: Simulate current schedule
- 5: Convert schedule into event-feature table
- 6: Extract bus-level features
- 7: Apply Rule-Based Scoring scorer to identify weak or high-impact buses
- 8: Destroy phase: remove trips linked to selected buses
- 9: Repair phase: reinsert removed trips heuristically by time order
- 10: Re-simulate updated schedule
- 11: Compute annual total cost
- 12: **if an** improved solution is obtained, then
- 13: Accept updated solution
- 14: **else**
- 15: Keep previous solution
- 16: **end if**
- 17: Repeat until maximum iterations are reached
- 18: Output best RBS-LNS schedule

$$\mathbf{f}_i = [n_i^{load}, n_i^{dead}, n_i^{chg}, n_i^{wait}, 1] \quad (29)$$

A Rule-Based Scoring function assigns an inefficiency score:

$$s_i = \sigma(\mathbf{w}^\top \tilde{\mathbf{f}}_i) \text{ where } \sigma(z) = \frac{1}{1 + e^{-z}} \quad (30)$$

And $\tilde{f}_i$ denotes normalized features. A fraction ρ of buses with the highest scores is selected:

$$\mathcal{B}_{destroy} = \text{TopK}(\{s_i\}_{i \in \mathcal{B}}, \lceil \rho \mid \mathcal{B} \rceil) \quad (31)$$

Trips served by these buses are removed:

$$\mathcal{T}_{destroy} = \bigcup_{i \in \mathcal{B}_{destroy}} \mathcal{T}(i) \quad (32)$$

After destruction, standalone RBS-LNS typically performs heuristic repair (e.g., reinserting trips in time order with greedy bus selection). This can improve schedules but may not be optimal in the repair step and may struggle under strict timetable constraints when charging congestion is significant. It should be noted that the proposed TLH-EBS framework is not formulated as a classical Tri-Level mathematical programming problem involving nested upper-, middle-, and lower-level optimization models. Instead, the framework employs a hierarchical three-stage hybrid optimization strategy in which PSO, RBS-LNS, and MILP repairs are executed sequentially and cooperatively. The term “Tri-Level” therefore refers to the three decision-making layers of the optimization process rather than a formal Tri-Level mathematical programming structure. This hierarchical decomposition improves computational tractability while enabling coordinated optimization of infrastructure, scheduling, and operational decisions.

5.4. Proposed Hybrid: TLH-EBS (Tri-Level Hybrid Electric Bus Scheduling)

TLH-EBS hybridizes PSO, RBS-LNS, and MILP by assigning each level a distinct mathematical role: PSO explores the global macro-decision space, RBS-LNS creates a large neighborhood by targeted destruction, and MILP produces exact repair within that neighborhood, as shown in Algorithm 4. The hybrid iteration can be represented as an operator composition:

$$(\mathcal{S}^{k+1}, x^{k+1}) = \mathcal{L}(\mathcal{R}_{MILP}(\mathcal{D}_{Neural}(\mathcal{P}_{PSO}(x^k)))) \quad (33)$$

where $\mathcal{P}_{PSO}$ outputs a macro decision vector x , $\mathcal{D}_{Neural}$ destroys a subset of trips $\mathcal{T}_{destroy}$, $\mathcal{R}_{MILP}$ repairs them exactly, and $\mathcal{L}$ is a local refinement (local PSO).

5.4.1. Simulation Model Embedded in TLH-EBS

For any candidate decision vector x , schedules are generated by strict simulation. Energy needed for a passenger trip t by type b :

$$E_t^{load}(b) = \alpha_b L_t \quad (34)$$

Energy for deadheading between stand s and depot $d(s)$:

$$E_{s \rightarrow d}^{dead}(b) = \beta_b L_{s,d(s)} \quad (35)$$

A trip is feasible only if the SOC before departure satisfies:

$$SOC \geq E_t^{load}(b) + E_{d_t \rightarrow d(d_t)}^{dead}(b) + SOC_b^{res} \quad (36)$$

With reserve modeled as:

$$SOC_b^{res} = (\phi_0 + \phi_r) E_b^{max} \quad (37)$$

where ϕ_0 is the fixed base reserve and ϕ_r is the optimized reserve-extra fraction. Charging trigger is:

$$SOC \leq \phi_c E_b^{max} \Rightarrow \text{send bus to depot for full charge} \quad (38)$$

Algorithm 4 Proposed Hybrid: TLH-EBS

```

1: Initialize route, depot, bus, charger, and timetable data
2: Generate all scheduled trips for Type-1 and Type-2 electric buses
3: Define objective function to minimize annual total scheduling cost:
      M = M1 + M2 + M3 + M4 + M5
4: Initialize global solution using Particle Swarm Optimization (PSO)
5: for each PSO particle do
6:   Decode particle into bus scheduling policy and charger allocation
7:   Simulate full-day electric bus operation
8:   Check strict timetable feasibility and SOC feasibility
9:   if SOC is insufficient for the next trip and nearest depot reachability, then
10:    Send the bus to the nearest depot for charging
11:    if the charger slot is unavailable, then
12:      Wait until the charger becomes free
13:    end if
14:    Perform full charging cycle
15:    Return the bus to the corresponding bus stand
16:  end if
17:  Compute fleet size, loaded trips, deadheading trips, charging events, and
  annual cost
18:  Update personal best and global best solutions
19: end for
20: Obtain initial best schedule from PSO
21: Simulate complete schedule and convert events into feature table
22: for each Hybrid-LNS iteration do
23:   Extract bus-level operational features
24:   Apply Rule-Based Scoring scorer to identify weak or high-cost buses
25:   Destroy phase: remove trips assigned to the selected buses
26:   Apply MILP repair phase to optimally reassign removed trips
27:   Merge repaired trips with remaining schedule
28:   Apply local PSO refinement around the current best decision
29:   Re-simulate updated schedule
30:   if the updated annual cost is improved, then
31:     Accept the updated solution as the current best
32:   else
33:     Retain previous best solution
34:   end if
35:   Check restart or iteration stopping criterion
36: end for
37: Return the final hybrid best solution
38: Output fleet size, charger allocation, loaded trips, deadheading trips, charging
  events, and annual cost

```

Charging duration for adding E_{add} energy with charger power P_b :

$$t^{chg} = \left\lceil \frac{E_{add}}{P_b} \times 60 \right\rceil \quad (39)$$

If the depot has C_{db} chargers and current overlapping bookings exceed capacity, a waiting time t^{wait} is generated such that:

$$t^{wait} = \min\{\delta \geq 0 : \text{available charger in } [\tau + \delta, \tau + \delta + t^{chg}]\} \quad (40)$$

This waiting feeds back into bus availability and may violate strict departure times. If strict departure becomes infeasible, a new bus is spawned, which directly increases N_b and capital cost.

During simulation, each scheduled departure is evaluated sequentially according to timetable feasibility, charger availability, and battery state-of-charge constraints. If the available battery energy is sufficient to complete the scheduled passenger trip and subsequently reach the nearest charging depot while maintaining the minimum reserve SOC threshold, the vehicle is assigned to the trip. Otherwise, the bus is routed to the nearest depot for charging. Charging duration is determined based on the required charging energy and the charger power rating. If all chargers at the selected depot are occupied, the vehicle enters a waiting state until the earliest charger becomes available, and the resulting waiting duration is added to the vehicle availability time. When no existing vehicle can satisfy a scheduled departure due to insufficient SOC, charging delays, or charger waiting, a reserve bus is deployed to preserve strict timetable adherence. Throughout the simulation process, all operational events, including passenger-service trips, deadheading movements, charging events, waiting periods, and terminal layovers, are recorded with their associated start time, end time, travel distance, energy consumption, and SOC transition. This event-based simulation logic enables the TLH-EBS framework to capture realistic operational interactions while maintaining computational efficiency for large-scale district transit scheduling problems.

5.4.2. MILP Repair Subproblem in TLH-EBS

After RBS-LNS destroys trips, the repair set $\mathcal{T}_{destroy}$ is repaired using an exact packing MILP. Let $K_r = \{1, \dots, |\mathcal{T}_{destroy}|\}$ repair buses and decision variable y_{tk} assign trip t to repair a bus k . The repair objective is:

$$\min \sum_{k \in K_r} u_k \quad (41)$$

Subject to:

$$\sum_{k \in K_r} y_{tk} = 1 \forall t \in \mathcal{T}_{destroy} \quad (42)$$

$$y_{tk} \leq u_k \forall t, k \quad (43)$$

And non-overlap:

$$y_{tk} + y_{t'k} \leq 1 \forall k, \forall (t, t') : \chi_{tt'} = 0 \quad (44)$$

This MILP returns a repaired ordering with minimum additional buses in the destroyed neighborhood, which is then merged back with the remaining schedule to form a new schedule $\mathcal{S}^{k+1}$.

5.4.3. Local PSO Refinement and Acceptance Rule

After repair, TLH-EBS performs a local PSO search around the current best macro vector x^{best} using a bounded perturbation radius ϵ :

$$x^{trial} = x^{best} + \epsilon \odot u, u \sim U(-1, 1) \quad (45)$$

A trial is accepted if it yields a lower annual cost:

$$M(x^{trial}) < M(x^{best}) \Rightarrow x^{best} \leftarrow x^{trial} \quad (46)$$

Convergence can be stated as

$$|M^{k+1} - M^k| < \varepsilon \text{ or } k \geq k_{\max} \quad (47)$$

The PSO optimizes macro variables that control congestion and feasibility; RBS-LNS changes the discrete structure of schedules by creating large neighborhoods; MILP ensures that the repair inside the neighborhood is exact and time-feasible. This Tri-Level hybrid structure reduces both structural waste (unnecessary buses) and infrastructure mismatch (excess chargers) while preserving strict departure constraints.

6. Computational Results and Discussion

6.1. Experimental Setup

The computational experiments evaluate the proposed Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework against three standalone approaches—MILP, PSO, and RBS-LNS—under realistic district-scale operations in Madurai. All computational experiments have been implemented in Python 3.11 and executed on a workstation equipped with a 13th Gen Intel(R) Core (TM) i7-1360P (2.20 GHz), 16 GB RAM, and Windows 11 operating system. The PSO component has utilized a swarm size of 16 particles and a maximum of 20 iterations. The RBS-LNS module has employed a destruction ratio of 12% and a maximum of 12 neighborhood search iterations. The MILP repair stage is solved using a maximum solver time limit of 5 s for each repair subproblem. These parameter values are selected based on preliminary tuning experiments to balance solution quality and computational efficiency.

The network consists of three interconnected bidirectional corridors (T–A, A–M, and M–T) operating continuously from 05:00 AM to 12:30 AM with a mandatory 10 min terminal layover and strict headway requirements. All solutions are assessed using the same annualization assumptions, where capital expenditure is converted into equivalent annual cost using an interest rate of 9% and a project lifetime of 12 years, while electricity cost is calculated under the TNERC tariff of INR 8.10/kWh (USD 0.086/kWh) and annualized over 365 operating days. The simulation strictly enforces timetable feasibility; when an assigned bus cannot meet a departure due to SOC shortage or charging delay, an additional bus must be deployed, and it directly increases annualized fleet capital cost. The evaluation includes two complementary result layers. First, a primary comparison is performed using the optimized configuration outputs (fleet sizes, charger counts, deadheading, charging events, and annual cost) across the four methods. Second, robustness is assessed by examining algorithm performance over twelve scenarios formed by the cross-product of discharge depth and charger power, enabling statistical comparison of solution consistency and reliability. Performance indicators include annual total cost, cost component breakdown, fleet size, charging infrastructure requirement, charging frequency, deadheading distance, and runtime.

The stopping criterion for PSO is the maximum iteration limit, whereas RBS-LNS is terminated after reaching the predefined neighborhood search iterations. The hybrid TLH-EBS framework is terminated when all PSO iterations, RBS-LNS iterations, and MILP repair stages are completed without further improvement in the objective function. In addition to solution quality, computational runtime is recorded for all optimization methods to evaluate algorithmic scalability and practical applicability.

6.2. Fleet Size and Infrastructure Comparison

Fleet size and charger allocation directly determine both the capital cost and the schedule feasibility, especially under strict headway constraints. The standalone MILP solution requires 76 Type-1 buses and 88 Type-2 buses. The partial schedule of electric buses of both types is shown in Figure 13. Although MILP is effective in constructing time-feasible trip packings, it tends to increase fleet size when charging congestion and SOC feasibility cannot be globally coordinated, because the model's practical implementation is typically constrained to partial packing and cannot fully represent coupled charging–SOC–timetable dynamics at the district scale.



Figure 13. Schedules of partial electric buses for both types (MILP).

By contrast, PSO has reduced the required buses slightly to 75 Type-1 and 83 Type-2, indicating that macro-level search over infrastructure and operational policy can reduce over-provisioning by improving charging feasibility. The partial schedule of electric buses of both types is shown in Figure 14.



Figure 14. Schedules of partial electric buses for both types (PSO).

RBS-LNS has resulted in 73 Type-1 and 84 Type-2, suggesting that the schedule restructuring improves utilization for one fleet type while still requiring more support

vehicles to preserve timetable feasibility in other parts of the network. The partial schedule of electric buses of both types is shown in Figure 15.



Figure 15. Schedules of partial electric buses for both types (RBS-LNS).

The proposed TLH-EBS framework has achieved the smallest fleet requirement of 70 Type-1 and 79 Type-2, demonstrating that hybrid coordination reduces “hidden slack buses” that are typically added to absorb charging delays or SOC infeasibilities. This improvement can be interpreted as a structural effect of the Tri-Level design: PSO first pushes the solution toward better charger-policy regimes, RBS-LNS then identifies inefficient bus chains and removes them, and MILP repair reconstructs the removed part with minimal additional buses under strict time constraints. The partial schedule of electric buses of both types is shown in Figure 16. The charger allocations also show that TLH-EBS achieves feasibility with fewer chargers than MILP and a more balanced distribution than the standalone RBS-LNS, meaning it avoids both over-building (capital waste) and under-building (charging congestion).



Figure 16. Schedules of partial electric buses for both types (TLH-EBS).

6.3. Annual Cost Comparison

The annual total scheduling costs demonstrate a clear dominance of TLH-EBS, as shown in Figure 17. The annualized cost obtained with standalone MILP is INR 35.43 crores (USD 3,748,131), standalone PSO yields INR 34.03 crores (USD 3,600,011), standalone RBS-LNS yields INR 34.36 crores (USD 3,634,819), and TLH-EBS achieves the lowest annual cost of INR 33.05 crores (USD 3,487,025), as shown in Table 2.

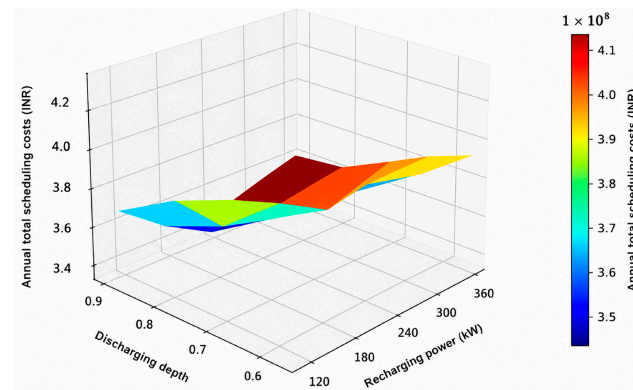


Figure 17. Impact of discharging depth and charging power on annual total scheduling cost.

Table 2. Comparison of optimization results.

Related Indicators	MILP	PSO	RBS-LNS	TLH-EBS
Electric Bus Type-1	76	75	73	70
Electric Bus Type-2	88	83	84	79
Charger Type-1 (240 kW)	9	6	7	6
Charger Type-2 (120 kW)	12	10	17	9
Recharging trips	66	74	70	69
Deadheading distance Type-1 (km)	322	371	369	360
Deadheading distance Type-2 (km)	413	388	347	370
Passenger distance Type-1 (km)	8142	8142	8142	8142
Passenger distance Type-2 (km)	7788	7788	7788	7788
Annualized total cost M in (INR) and (USD)	INR 35,43,12,983 (USD 3,747,568.42)	INR 34,02,82,055 (USD 3,599,163.30)	INR 34,35,53,588 (USD 3,633,766.30)	INR 33,05,37,486 (USD 3,487,025.29)

Among the standalone methods, PSO performs best, and it is consistent with the fact that the charger allocation and charging policy strongly influence feasibility and fleet requirement. However, PSO alone cannot always remove deep structural inefficiencies in trip chains, especially those arising from charging wait cascades that propagate through the timetable.

The absolute annual cost reduction of TLH-EBS related to the best standalone method (PSO) is:

$$\Delta M = M_{PSO} - M_{TLH-EBS} = \text{INR } 34,02,82,055 - \text{INR } 33,05,37,486 = \text{INR } 97,44,569 \quad (48)$$

And the percentage improvement is:

$$\%Improvement = \frac{M_{PSO} - M_{TLH-EBS}}{M_{PSO}} \times 100 \approx 2.8\% \quad (49)$$

Although 2.8% may appear moderate, in annualized fleet operations, these savings repeat every year; over a 12-year horizon and even without escalation, the cumulative savings are substantial. More importantly, the improvement is achieved while strictly meeting timetable constraints, and it means that the savings do not come from relaxing service quality.

6.4. Cost Component Analysis

A cost component breakdown between PSO and TLH-EBS reveals how the hybrid framework achieves savings. The annualized bus capital cost decreases from INR 20.31 crores (USD 2,128,9) to INR 19.15 crores (USD 2,008,055), corresponding to a 5.77% reduction. This is the dominant contributor and is directly tied to fleet size reduction achieved through hybrid restructuring. Charger capital cost also reduces from INR 0.726 crores (USD 76,101) to INR 0.691 crores (USD 72,432) (a 4.81% reduction), reflecting that TLH-EBS improves charger utilization efficiency and reduces redundant installations while maintaining feasibility. Electricity cost increases slightly (−1.96% “improvement” value indicates an increase), which is a realistic and interpretable outcome: TLH-EBS tends to utilize batteries more deeply and runs buses more efficiently with fewer spares, meaning a larger fraction of work is performed by fewer buses with potentially more energy throughput.

However, this increase is economically outweighed by the substantial capital savings from the reduced bus procurement. Deadheading cost decreases marginally, indicating that the hybrid solution also reduces certain non-revenue movements through better chain formation and depot-return decisions with a 3.7% reduction. Passenger service cost remains unchanged because the passenger-kilometer service requirement is fixed by timetable demand; optimization affects how service is delivered, not how much service is delivered. Overall, the component-wise evidence confirms that TLH-EBS primarily improves economic performance by reducing fleet and infrastructure investment needs while preserving strict timetable compliance, as shown in Table 3. Although the proposed TLH-EBS framework achieves a seemingly modest annual cost reduction of 2.8% relative to the best standalone optimization method, this improvement corresponds to an absolute annual saving of approximately INR 97.44 lakhs (USD 102,817.35). Over the assumed 12-year project lifetime, the cumulative savings exceed INR 11.69 crores (USD 1,233,480.73) without accounting for inflation or energy price escalation. From a social perspective, improved timetable adherence enhances service reliability and reduces passenger waiting time, particularly benefiting middle- and lower-income populations that rely heavily on public transportation. Economically, the reduction in fleet procurement and charging infrastructure investment lowers capital expenditure requirements for transport operators. Environmentally, improved fleet utilization reduces energy waste and indirectly contributes to lower greenhouse gas emissions. From an energy management perspective, improved charger utilization and reduced charging congestion enhance the operational efficiency of electric bus systems.

6.5. Sensitivity Analysis

Sensitivity analysis evaluates how operational policies and infrastructure intensity influence annual cost. The scenario table varying discharge depth (60–90%) and charging power (60–360 kW) shows that increasing allowable discharge depth generally reduces total annual cost because it increases usable energy per cycle and delays depot charging events, which reduce mid-day charging congestion and the need for spare buses, as shown in Figure 18. The results indicate that cost values decline significantly as discharge depth rises from 60% to 90% across most charging power levels, as shown in Table 4. Charging power produces a trade-off. Higher charging power reduces charging duration and waiting, im-

proving timetable feasibility and enabling a lower fleet size, but it requires a higher charger investment. Thus, the cost curve is not monotonic; beyond a certain point, infrastructure cost offsets operational benefits. In the scenario table, the lower-cost region tends to appear around higher discharge depth with medium-to-high charging power (not necessarily the maximum). This supports an important planning insight: the most economical system is achieved not by maximizing charging power, but by balancing charging speed with capital expenditure while taking advantage of deeper usable battery energy.

Table 3. Detailed comparison of cost components of PSO vs. TLH-EBS.

Cost Component	Cost Result in INR and USD		Reduction in INR and USD	Improvement (%)
	PSO	TLH-EBS		
Annualized Bus Capital Cost (M1)	INR 20,31,87,800 (USD 2,148,542.43)	INR 19,14,61,400 (USD 2,024,545.92)	INR 1,17,26,400 (USD 123,996.51)	5.77
Annualized Charger Capital Cost (M2)	INR 72,59,200 (USD 76,759.78)	INR 69,10,200 (USD 73,069.85)	INR 3,49,000 (USD 3689.93)	4.81
Electricity Cost (M3)	INR 11,93,85,835 (USD 1,262,407.21)	INR 12,17,25,609 (USD 1,287,148.49)	−INR 23,39,774 (−USD 24,741.28)	−1.96
Deadheading Cost (M4)	INR 2,41,630 (USD 2555.04)	INR 2,32,687 (USD 2460.47)	INR 8943 (USD 94.57)	3.7
Passenger Service Cost (M5)	INR 1,02,07,590 (USD 107,936.87)	INR 1,02,07,590 (USD 107,936.87)	INR 0 (USD 0.00)	0
Annualized Total Cost (M)	INR 34,02,82,055 (USD 3,598,201.33)	INR 33,05,37,486 (USD 3,495,161.6)	INR 97,44,569 (USD 103,039.73)	2.8

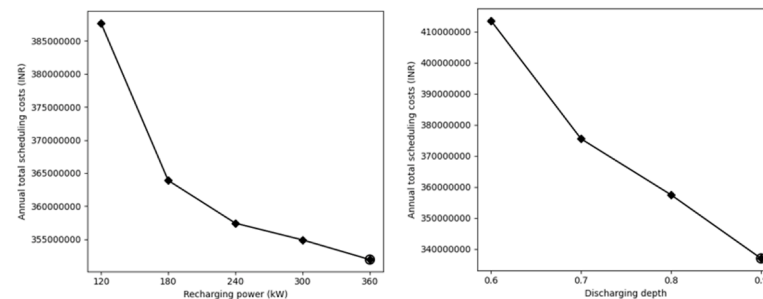


Figure 18. The impact of recharging power and discharging depth on annual total scheduling costs.

Table 4. Impact of discharging depth and charging power on annual total scheduling cost (INR and USD).

Discharging Depth	Recharging Power (kW)					
	60	120	180	240	300	360
60%	INR	INR	INR	INR	INR	INR
	43,54,98,503↑	42,05,27,498	41,35,21,839	39,52,07,368	40,66,25,704	39,71,03,272
	(USD 46,051,842)	(USD 44,466,515)	(USD 43,725,752)	(USD 41,789,173)	(USD 42,996,554)	(USD 41,990,323)

Table 4. Cont.

Discharging Depth	Recharging Power (kW)					
	60	120	180	240	300	360
70%	INR 40,09,60,998 (USD 42,401,368)	INR 38,91,29,089 (USD 41,146,801)	INR 37,54,77,675 (USD 39,703,007)	INR 37,91,55,274 (USD 40,091,820)	INR 38,01,20,162 (USD 40,193,822)	INR 37,47,39,260 (USD 39,625,123)
	INR 38,76,72,176 (USD 40,992,442)	INR 36,38,96,010 (USD 38,478,348)	INR 35,72,27,378 (USD 37,772,654)	INR 35,74,27,986 (USD 37,793,825)	INR 35,49,04,954 (USD 37,527,113)	INR 35,19,34,514 (USD 37,213,541)
	INR 36,84,24,367 (USD 38,956,988)	INR 34,97,12,539 (USD 36,978,635)	INR 34,40,99,499 (USD 36,384,179)	INR 33,69,45,174↓ (USD 35,628,495)	INR 33,89,41,280 (USD 35,839,493)	INR 33,80,52,533 (USD 35,745,513)

Table 4 presents the sensitivity analysis performed exclusively for the proposed TLH-EBS framework to investigate the influence of battery discharge-depth constraints and charger power ratings on annual scheduling cost and infrastructure requirements. All results reported in this table correspond to the optimized solutions obtained using the proposed tri-level hybrid framework.

6.6. Comparison with Diesel-Based Operation

To evaluate the practical economic advantages of electric bus deployment, the optimized electric bus system obtained using the TLH-EBS framework is compared with a conventional diesel-based operation under identical operational conditions. The comparison assumes the same route network, trip timetable, service frequency, and passenger demand levels used in the electric bus scheduling experiments. By maintaining identical service commitments, the analysis ensures that differences in cost arise solely from the underlying propulsion technology and scheduling efficiency rather than from changes in service supply. To improve the transparency and reproducibility of the diesel comparison, the principal assumptions and cost components associated with the equivalent diesel fleet are summarized in Table 5. The diesel benchmark adopts the same system boundary as the optimized electric bus system, including identical routes, service frequencies, passenger demand, daily scheduled trips, and annual operating distances. Consequently, the resulting economic differences reflect only the influence of propulsion technology and operational strategy rather than variations in service provision. The comparison assumes a fleet of contemporary 12 m BS-VI low-floor diesel transit buses with a procurement cost of INR 60 lakhs (USD 63,332.88) per vehicle and a diesel retail price of INR 100.30/liter (USD 1.06/liter), representing prevailing market conditions during the preparation of this study.

When this cost is aggregated across the entire fleet required to serve the Madurai district network, the total annual fuel expenditure alone becomes substantial. In addition to fuel, diesel buses incur significant maintenance costs due to periodic engine servicing, lubrication requirements, transmission wear, and emission control system maintenance. These mechanical complexities lead to higher lifecycle operational costs compared to electric drivetrain systems. Based on the operational scale of the study network and typical diesel fleet operating parameters, the estimated total annual operating cost of diesel-based operation ranges between INR 48.79 crores/year (USD 5,150,790/year). This estimate includes vehicle capital recovery, fuel expenditure, and maintenance costs. In contrast, the optimized electric bus system obtained using the proposed TLH-EBS framework results

in an annual total scheduling cost, which includes annualized electric bus capital cost, charging infrastructure investment, electricity consumption cost, deadheading cost, and passenger service cost. The percentage reduction in annual operational cost achieved by the optimized electric system related to diesel operation can therefore be calculated as:

$$\text{Cost Reduction (\%)} = \frac{C_{\text{Diesel}} - C_{\text{Electric Bus}}}{C_{\text{Diesel}}} \times 100 = \frac{48.79 - 33.05}{48.79} \times 100 \approx 32.3\% \quad (50)$$

Table 5. Assumptions and cost components for equivalent diesel-based operations.

Parameter	Value
Equivalent diesel fleet size	149 buses
Diesel bus type	12 m BS-VI low-floor transit bus
Passenger capacity	70–75 passengers
Vehicle purchase cost per bus	INR 60 lakh (USD 63,332.88)
Vehicle lifetime	12 years
Interest rate	9%
Capital recovery factor (CRF)	0.1407
Annualized vehicle capital cost	INR 12.58 crore/year (USD 1,320,004)
Annual operating distance	5.81 million km/year
Diesel fuel efficiency	3.8 km/L
Annual diesel consumption	1.53 million liters/year
Diesel retail price	INR 100.30/liter (USD 1.052/liter)
Annual fuel cost	INR 15.35 crore/year (USD 1,610,60)
Annual maintenance cost	INR 11.92 crore/year (USD 1,250,708)
Annual driver and staff cost	INR 8.94 crore/year (USD 938,000)
Total annual diesel operating cost	INR 48.79 crore/year (USD 5,119,300)

As shown in Table 5, fuel expenditure represents the largest component of annual diesel operating costs, accounting for approximately 31.5% of the total annual expenditure. Annual maintenance expenses contribute an additional 24.4%, reflecting higher servicing requirements associated with internal combustion engines, lubrication systems, transmission wear, and exhaust after-treatment systems required for BS-VI emission compliance. Driver and operational staff costs account for approximately 18.3% of the total annual cost, while annualized vehicle capital recovery contributes the remaining 25.8%. By contrast, battery electric buses benefit from higher drivetrain efficiency and reduced mechanical complexity, resulting in lower lifecycle operating costs, despite higher initial capital investment. Under identical service requirements and operational boundaries, the optimized TLH-EBS framework reduces annual operating expenditure from INR 48.79 crores (USD 5,117,351) for the equivalent diesel fleet to INR 33.05 crores (USD 3,466,456), corresponding to an annual cost reduction of approximately 32.3%. In addition to these economic benefits, the transition to electric buses substantially reduces fossil fuel dependency and improves the long-term sustainability of district-level public transportation systems. An important observation is that these savings are achieved without altering service frequency or passenger capacity. The scheduling optimization strictly maintains the original timetable and headway structure, ensuring that the passenger service levels remain unchanged. Consequently, the cost advantage arises entirely from improved operational efficiency and lower energy and

maintenance costs associated with electric buses. From an operational perspective, electric buses benefit from higher drivetrain efficiency, reduced mechanical complexity, and lower energy cost per kilometer.

While the initial capital investment for electric buses and charging infrastructure is higher than that of diesel buses, the lifecycle cost advantage becomes evident when energy and maintenance costs are considered over long-term operations. From a policy standpoint, these results strongly support the ongoing electrification initiatives under the Tamil Nadu Electric Vehicle Policy 2023 and the FAME-II scheme, which aim to accelerate electric bus adoption in public transport systems.

The findings demonstrate that the integrated optimization of fleet scheduling and charging infrastructure is essential to fully realize the economic benefits of electric bus deployment. Overall, the comparison confirms that the district-level electrification of public bus fleets, when supported by advanced scheduling frameworks such as TLH-EBS, can significantly reduce operational costs while maintaining service reliability and passenger accessibility. The diesel bus specifications correspond to typical 12 m urban buses currently used by state transport undertakings in India, while the electric bus specifications reflect commercially deployed battery-electric buses operating under depot-charging configurations.

The computational evidence shows that the standalone approaches improve the performance only partially because each one optimizes a limited part of the coupled decision space. MILP provides strong feasibility in time packing but cannot practically scale when SOC and charging congestion are modeled at full resolution. PSO explores charger allocation and charging policy globally, but does not inherently rebuild inefficient trip chains once a schedule structure is formed. RBS-LNS is effective in restructuring, but when operating alone with heuristic repair, it cannot guarantee optimal reinsertion under strict departure constraints. TLH-EBS succeeds because its levels are complementary and staged: PSO reduces macro-level infeasibility and infrastructure mismatch, RBS-LNS creates a targeted large neighborhood by removing inefficient bus chains, and MILP repair reconstructs these removed segments exactly while minimizing additional bus usage. This structured synergy explains why TLH-EBS simultaneously reduces fleet size and annual cost while maintaining strict timetable feasibility. In addition to the economic advantages, the proposed electric bus scheduling framework provides substantial environmental benefits. In this study, diesel-based equivalent operations refer to a hypothetical diesel bus fleet operating under exactly the same operational conditions as the optimized electric bus system, including identical routes, service frequencies, trip schedules, passenger demand levels, and annual operating distances. By maintaining an identical service boundary, the comparison isolates the economic impact of propulsion technology and scheduling strategy rather than differences in service provision. The reported cost reduction of approximately 32.3% is therefore specific to the Madurai district case study, and it should not be interpreted as a universally guaranteed value for all transit systems, since the actual savings depend on local fuel prices, electricity tariffs, vehicle procurement costs, maintenance practices, and operational conditions.

Sustainability Benefits Assessment

Beyond the economic advantages, the proposed TLH-EBS framework provides substantial environmental and societal benefits through the electrification of district-level public transportation systems. Based on the optimized scheduling solution, the total daily passenger-service distance reaches approximately 15,930 km, corresponding to an annual operational distance of approximately 5.81 million km. Assuming an average diesel bus fuel efficiency of 3.8 km/L, an equivalent diesel fleet operating under identical service conditions would consume approximately 1.53 million liters of diesel annually.

Using a standard diesel emission factor of 2.68 kg CO₂ per liter of fuel consumed, the equivalent diesel-based operation would generate approximately 4100 tonnes of direct tailpipe CO₂ emissions per year. In contrast, the proposed electric bus system completely eliminates tailpipe emissions during vehicle operation, thereby significantly reducing local air pollution and improving urban environmental quality. Furthermore, the removal of combustion-related emissions contributes to lower concentrations of particulate matter (PM), nitrogen oxides (NO_x), and sulfur oxides (SO_x), thereby enhancing the environmental sustainability of district-level public transportation systems and improving public health outcomes.

When indirect electricity generation emissions are considered, the overall environmental performance depends on the regional electricity generation mix. Based on the annual electricity expenditure obtained from the optimized TLH-EBS solution and the adopted electricity tariff of INR 8.10/kWh (USD 0.085/kWh), the corresponding annual electricity consumption is estimated to be approximately 15.03 million kWh. Consequently, the transition from diesel buses to electric buses is expected to reduce annual carbon dioxide emissions by approximately 45–60%, depending on the carbon intensity of grid electricity. Additional reductions in lifecycle emissions can be achieved through the integration of renewable-energy-assisted depot charging systems, photovoltaic generation, and cleaner electricity procurement strategies.

Beyond the environmental improvements, the proposed framework also contributes to broader sustainability objectives. From a social sustainability perspective, strict timetable adherence and improved service reliability enhance public transport accessibility, particularly for low- and middle-income populations that rely heavily on district-level bus services in Madurai. From an economic sustainability perspective, optimized fleet sizing and charging infrastructure allocation result in substantial long-term operational cost savings over the project lifetime. From an energy sustainability perspective, the framework reduces dependence on imported fossil fuels while facilitating the transition of public transportation systems toward electrified and energy-efficient mobility solutions.

6.7. Statistical Validation of Algorithm Performance

To validate that the observed performance advantages are not scenario-specific or due to random variation, statistical testing has been conducted across 12 scenarios based on discharge depth (DoD) and charging power (P). The Friedman non-parametric test evaluates whether multiple algorithms differ significantly in performance when tested on repeated comparable cases. The test yields a Friedman chi-square statistic of $Q = 16.5$ with a p -value of $p = 0.000895$. Since $p < 0.05$, the null hypothesis, that all algorithms have equivalent performance, is rejected, confirming that the algorithm choice materially impacts cost outcomes.

Ranking-based results further reinforce this conclusion. The Hybrid (TLH-EBS) method achieves the best (lowest) Friedman average rank of 1.3333, while PSO achieves 2.3333, RBS-LNS 3.0833, and MILP 3.2500. Consistent rankings across Friedman, aligned Friedman, and Quade methods indicate that the hybrid framework dominates not only in best-case performance but also in systematic robustness, as shown in Table 6. Post hoc Holm analysis compares TLH-EBS against each competing method by using adjusted p -values to control family-wise error.

Table 6. Comparison of Friedman, aligned Friedman, and Quade ranks.

Algorithm	Friedman Average Rank	Aligned Friedman Average Rank	Quade Average Rank
MILP	3.2500	3.2500	20.6667
PSO	2.3333	2.3333	15.4167
RBS-LNS	3.0833	3.0833	21.3333
Hybrid	1.3333	1.3333	7.5833

The results show a statistically significant improvement of TLH-EBS over MILP (Holm-adjusted $p = 0.0008$) and RBS-LNS ($p = 0.0018$). The TLH-EBS vs. PSO comparison is marginal ($p = 0.0578$), indicating that PSO is the strongest standalone competitor and the hybrid advantage emerges primarily through structural schedule repair improvements in many but not in all scenarios.

The proposed TLH-EBS framework has consistently achieved the lowest annual scheduling cost among all the evaluated methods. Statistical analysis has confirmed significant improvements related to MILP and RBS-LNS approaches, whereas the improvement related to PSO, although economically favorable, has not achieved statistical significance at a 95% confidence level after the adjustment for multiple comparisons (adjusted p -value = 0.0578), as shown in Table 7.

Table 7. Holm–Bonferroni post hoc test results comparing hybrid method with benchmark algorithms.

Comparison	Test Statistic (z-Value)	Raw p -Value	Holm-Adjusted p -Value	Better Method
Hybrid vs. MILP	3.6366	0.0003	0.0008	Hybrid
Hybrid vs. RBS-LNS	3.3204	0.0009	0.0018	Hybrid
Hybrid vs. PSO	1.8974	0.0578	0.0578	Hybrid

Since PSO, RBS-LNS, and the proposed TLH-EBS framework incorporate stochastic search mechanisms, solution quality may vary slightly across independent executions due to the differences in population initialization, neighborhood exploration, and randomized search operations. To evaluate algorithm robustness and convergence stability, each stochastic optimization method is executed over 30 independent runs using different random seeds under identical operational scenarios and parameter settings. For each algorithm, the mean annual scheduling cost, standard deviation, best and worst solutions obtained, average computational runtime, and runtime variability are recorded. The resulting performance statistics are summarized in Table 8.

The proposed TLH-EBS framework has consistently achieved the lowest average annual scheduling cost while exhibiting lower solution variability compared to the standalone PSO and RBS-LNS approaches. The reduced standard deviation observed for the hybrid framework indicates improved convergence stability and solution robustness across independent executions. Although the integration of multiple optimization stages results in a modest increase in computational time, the additional computational effort remains acceptable for strategic district-level planning applications and is compensated by improved solution quality and consistency. Furthermore, repeated independent executions have confirmed that the performance improvements of the proposed TLH-EBS framework are not solely attributable to favorable stochastic initialization but are consistently reproduced across multiple random seeds and independent runs.

Table 8. Robustness evaluation of stochastic optimization algorithms over multiple independent runs.

Algorithm	Independent Runs	Mean Annual Cost (INR Crore)	Std. Dev. (INR Crore)	Best Cost (INR Crore)	Worst Cost (INR Crore)	Mean Runtime (min)	Runtime Std. (min)
PSO	30	INR 34.12 (USD 3,591,579)	INR 0.09 (USD 9474)	INR 34.03 (USD 3,582,105)	INR 34.33 (USD 3,613,684)	28.4	1.6
RBS-LNS	30	INR 34.47 (USD 3,628,421)	INR 0.11 (USD 11,579)	INR 34.36 (USD 3,616,842)	INR 34.76 (USD 3,658,947)	34.2	2.1
TLH-EBS	30	INR 33.12 (USD 3,486,316)	INR 0.08 (USD 8421)	INR 33.05 (USD 3,478,947)	INR 33.29 (USD 3,504,211)	41.5	1.2

Scenario-wise results also show that TLH-EBS achieves the best minimum observed annual cost of INR 336,584,179.68 (USD 3,558,074.56) and the lowest mean cost across scenarios, as shown in Table 9, which provides a comparative evaluation of four optimization methods, namely MILP, PSO, FG-LNS, and TLH-EBS, under identical operational scenarios. Consequently, differences in annual costs of identical discharge-depth and charging-power combinations reflect variations in algorithmic search capability and solution quality rather than the differences in operational assumptions. Together, these statistical outcomes confirm that TLH-EBS provides a robust and repeatable performance advantage, strengthening the scientific credibility of the proposed framework.

Table 9. Scenario-wise statistical testing based on discharge depth and charging power.

Scenario	MILP	PSO	RBS-LNS	TLH-EBS
DoD 60 P 120	INR 41,49,45,948 (USD 4,374,775)	INR 40,97,48,588 (USD 4,320,019)	INR 41,73,74,176 ↑ (USD 4,400,376)	INR 40,85,16,976 (USD 4,307,025)
DoD 60 P 240	INR 39,77,97,718 (USD 4,193,792)	INR 39,43,18,347 (USD 4,157,298)	INR 39,58,34,413 (USD 4,173,282)	INR 39,45,49,299 (USD 4,159,733)
DoD 60 P 360	INR 40,33,24,058 (USD 4,252,246)	INR 39,86,25,498 (USD 4,202,709)	INR 40,66,37,537 (USD 4,287,180)	INR 39,07,76,669 (USD 4,120,031)
DoD 70 P 120	INR 39,00,94,068 (USD 4,112,762)	INR 39,47,54,015 (USD 4,161,892)	INR 38,50,91,415 (USD 4,059,919)	INR 38,41,31,373 (USD 4,049,807)
DoD 70 P 240	INR 38,10,97,116 (USD 4,017,907)	INR 37,62,45,879 (USD 3,966,756)	INR 37,53,17,082 (USD 3,934,310)	INR 36,91,25,359 (USD 3,891,689)

Table 9. Cont.

Scenario	MILP	PSO	RBS-LNS	TLH-EBS
DoD 70 P 360	INR	INR	INR	INR
	37,72,61,849	37,54,23,482	37,99,57,662	37,30,78,076
	(USD 3,977,472)	(USD 3,958,100)	(USD 4,005,894)	(USD 3,932,634)
DoD 80 P 120	INR	INR	INR	INR
	36,73,09,754	36,21,98,917	36,09,78,864	36,06,79,317
	(USD 3,872,547)	(USD 3,818,663)	(USD 3,805,790)	(USD 3,802,632)
DoD 80 P 240	INR	INR	INR	INR
	35,74,16,164	34,85,94,730	35,78,99,858	35,57,72,338
	(USD 3,768,239)	(USD 3,675,234)	(USD 3,773,338)	(USD 3,750,908)
DoD 80 P 360	INR	INR	INR	INR
	35,57,46,597	34,58,35,233	35,86,60,257	34,18,69,162
	(USD 3,750,636)	(USD 3,646,141)	(USD 3,781,355)	(USD 3,604,327)
DoD 90 P 120	INR	INR	INR	INR
	35,62,46,246	35,08,59,571	35,62,69,738	34,70,29,110
	(USD 3,755,904)	(USD 3,699,112)	(USD 3,756,152)	(USD 3,658,728)
DoD 90 P 240	INR	INR	INR	INR
	34,57,42,359	33,95,62,391	33,95,40,295	34,20,13,153
	(USD 3,645,162)	(USD 3,580,006)	(USD 3,579,773)	(USD 3,605,845)
DoD 90 P 360	INR	INR	INR	INR
	34,03,20,337	34,28,56,406	34,03,74,816	33,65,84,179 ↓
	(USD 3,587,997)	(USD 3,614,735)	(USD 3,588,572)	(USD 3,548,607)

A key concern in integrated electric bus scheduling is whether the additional complexity of a hierarchical optimization framework can be justified by the resulting performance improvement. Although the proposed TLH-EBS framework achieves a relatively modest annual cost reduction of 2.8% compared to the best standalone optimization method (PSO), the benefits of the Tri-Level structure extend beyond cost minimization alone. The electric bus scheduling problem considered in this study involves tightly coupled decisions related to fleet sizing, charger allocation, charging coordination, and timetable-constrained trip assignment. These decisions interact dynamically, where inefficient charger allocation increases charging congestion, charging congestion affects bus availability, and reduced availability subsequently increases fleet requirements.

Consequently, optimizing only one decision layer often leads to suboptimal system-wide performance. The proposed Tri-Level framework decomposes the scheduling problem into three complementary decision layers. At the strategic level, Particle Swarm Optimization (PSO) performs global exploration of charger allocation and charging policy parameters. At the tactical level, Rule-Based Scoring Large Neighborhood Search (RBS-LNS) identifies inefficient bus chains and restructures the schedule through targeted destruction and reconstruction of high-cost solution regions. At the operational level, MILP-based repair optimally reinserts removed trips while preserving strict timetable feasibility and minimizing additional fleet requirements. The coordination among these layers enables simultaneous improvement of infrastructure utilization and schedule efficiency. The effectiveness of the

Tri-Level structure is reflected not only in annual cost reduction but also in operational indicators. Compared to the standalone PSO approach, TLH-EBS reduces the required fleet size from 158 buses to 149 buses, representing a fleet reduction of approximately 5.7%. Similarly, charger requirements decrease while maintaining strict timetable compliance. Since fleet procurement constitutes the largest cost component in electric bus operations, these reductions generate substantial long-term economic benefits throughout the project lifetime. Hence, the proposed Tri-Level structure provides operational advantages that cannot be fully captured by annual cost comparisons alone.

7. Conclusions and Policy Implications

7.1. Conclusions

This study has developed and validated a Tri-Level Hybrid Electric Bus Scheduling (TLH-EBS) framework to address the integrated fleet sizing, charger allocation, and timetable-constrained scheduling problem for district-level electric bus operations. Unlike conventional diesel scheduling, electric bus deployment introduces tightly coupled constraints involving battery capacity, charging duration, charger congestion, and state-of-charge feasibility. These interdependencies create a multi-layer optimization problem that cannot be effectively solved using standalone mathematical programming or single metaheuristic approaches. The proposed TLH-EBS framework integrates Particle Swarm Optimization for macro-level infrastructure exploration, Rule-Based Scoring Large Neighborhood Search for adaptive schedule restructuring, and MILP-based exact repair for combinatorial feasibility restoration. This hierarchical coordination enables simultaneous optimization of infrastructure and operational decisions under strict timetable enforcement. Computational results of the Madurai district case study demonstrate that TLH-EBS achieves the lowest annual total scheduling cost of INR 33.05 crores (USD 3,487,025 USD), representing a 2.8% improvement over the best standalone approach (PSO). Cost component analysis indicates that the primary savings arise from a 5.77% reduction in annualized bus capital cost and a 4.81% reduction in charger capital cost, while maintaining strict departure adherence without penalty relaxation. Statistical validation using Friedman and Holm tests confirms that the performance improvement is statistically significant across twelve operational scenarios. When compared to the equivalent diesel-based operations under the identical service conditions, the optimized electric system demonstrates an annual cost reduction of approximately 32.3%. This confirms the long-term economic viability of the structured electric bus deployment at the district scale.

7.2. Policy and Managerial Implications

The findings of this study directly support Tamil Nadu's Electric Vehicle Policy 2023 and the state's target of electrifying 30% of its State Transport Undertaking (STU) bus fleet by 2030. While central government support through FAME II incentives reduces capital burden, the economic success of electrification ultimately depends on efficient fleet-charger coordination and strict operational planning. The results show that infrastructure over-provisioning does not necessarily minimize cost; instead, balanced charger allocation combined with deeper battery utilization yields better economic performance. For Gross Cost Contract (GCC)-based procurement models, where operators are compensated per kilometer, optimization-driven scheduling becomes even more critical to prevent excess fleet procurement and unnecessary capital expenditure. This study provides a quantitative decision-support framework that can guide state transport corporations in planning economically viable electric bus deployments beyond metropolitan areas and into district-level networks.

7.3. Limitations and Future Research

While the proposed framework demonstrates strong performance, certain limitations remain. Battery degradation and lifecycle replacement dynamics are not explicitly modeled. Travel time variability and stochastic traffic conditions are assumed to be deterministic. Opportunity charging and partial charging strategies are not incorporated, as the focus is on depot-based full-cycle charging. Additionally, real-time dynamic dispatch adjustments are beyond the scope of this study. Future research can extend this work by integrating battery degradation modeling, stochastic optimization under uncertain traffic conditions, and reinforcement learning-based adaptive destruction mechanisms within the hybrid framework. Scaling the methodology to metropolitan multi-depot networks and incorporating renewable energy-based charging strategies would further enhance the practical relevance. Although the proposed TLH-EBS framework demonstrates superior performance compared to the benchmark methods, it does not guarantee global optimality. The framework combines PSO-based exploration, RBS-LNS schedule restructuring, and MILP-based local repair within a hybrid search process. While the MILP repair stage provides exact solutions for the repaired subproblems, the overall optimization procedure remains heuristic in nature. Consequently, the final solution must be interpreted as a high-quality near-optimal solution rather than a globally optimal solution. Future research may investigate decomposition-based exact optimization approaches or hybrid exact-metaheuristic frameworks to provide stronger optimality guarantees for large-scale electric bus scheduling problems.

Author Contributions: P.K.M.: Writing—review and editing, Writing—original draft, Software, Methodology, Funding acquisition, Conceptualization; C.R.S.: Supervision, Project administration, Investigation; A.M.S.: Visualization, Software, Data curation; A.E.X.S.: Validation, Software, Formal analysis. All authors have read and agreed to the published version of the manuscript.

Funding: This research has received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors extend their due thanks to the Thiagarajar College of Engineering management, Madurai, India, for their extensive research facilities and the financial backing from Thiagarajar Research Fellowship (TRF) scheme (File.no: TCE/RD/TRF/2024/16 dated 9 February 2024) is gratefully acknowledged.

Conflicts of Interest: The authors declare no conflicts of interest.

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