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Integrated charging facility planning and charging scheduling for a rural battery electric bus system

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ABSTRACT

Efficient charging planning and scheduling are crucial for electric buses (e-buses) due to their limited range and extended charging times. This paper focuses on the problem of planning the charging infrastructure for a public transport network in a rural area. Due to longer routes and poor road conditions in rural areas, especially in developing countries, conventional diesel intercity bus services account for significant carbon emissions from bus transport. However, there is a gap in planning the electrification of rural bus systems, especially in terms of charging infrastructure planning. Accordingly, the aim of this research is to identify optimal charging schedules using an integrated modelling approach. In particular, an optimisation model is developed to simultaneously determine the optimum location and capacity of charging facilities, along with optimal charging schedules for e-buses. This model aims to minimise the costs associated with charging infrastructure and the electricity consumed by the buses, considering time of use (TOU) electricity tariffs. A real-world case study of Kalyana Karnataka Road Transport Corporation (KKRTC) in Karnataka, India is presented to test the efficacy of the developed model. For the considered scenario in the Kalburgi division (the largest division in KKRTC), with 11 depots and 887 bus routes, the model provides 52 optimal locations with a total of 82 opportunity chargers. According to the model, the feasible electrification level is 67.08% in the case of rural battery electric bus (BEB) systems for this division. Finally, a sensitivity analysis is presented to understand the effect of battery size and charger power on the results. The proposed approach offers operators a valuable tool for making optimal decisions regarding e-bus networks.

1. Introduction

Rapid decarbonisation of transport is crucial to achieving global climate goals, as the sector is responsible for 23% of global energy-related carbon dioxide (CO_2) emissions. Within this sector, road transport accounts for 70% of emissions, while the remainder is contributed by railways, aviation, and shipping. Encouraging a modal shift to public transport and converting bus fleets to battery electric buses (BEBs) are two key strategic priorities to decarbonise the road transport sector (Jaramillo et al., 2022). The need to accelerate BEB adoption is even more pertinent in countries like India where the share of greenhouse gas (GHG) emissions from road transport is above the global average of 92%. This includes a 15% contribution from internal combustion engine (ICE) buses that run on fossil fuels such as diesel and compressed natural gas (CNG) (TERI, 2024). BEBs avoid tailpipe emissions, operate almost noise-free, and have a higher energy efficiency than ICE buses (Uslu and Kaya, 2021). They also have lower lifecycle GHG emissions than ICE buses, even in countries like India, where over 70% of electricity is generated from coal (ITF, 2023).

BEBs have higher upfront costs, but these are offset in the long run by lower operating and maintenance (O&M) costs (Rogge et al., 2018). Rapidly declining battery prices are resulting in the lifecycle cost of electric buses (e-buses) being lower than that of ICE buses, depending on the operating context. BEB adoption is accelerating globally due to the environmental and cost benefits (BNEF, 2024). Significant progress has already been made in the planning and procurement of urban BEB fleets

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(Gadepalli et al., 2022a). This is because their relatively shorter range (kilometres (km) driven with 100% charge) requirements are adequately met by available BEB models (Gadepalli et al., 2022b). However, rural and intercity markets have witnessed limited BEB uptake, and in the Indian context, these markets make up about 64% of the total vehicle-km operated by all buses, with around 70% of the public bus fleet operating on such routes (Transit Intelligence, 2024). Developing a pathway to convert rural and intercity fleets to BEBs is crucial to achieving decarbonisation targets in India. This would also provide valuable learnings for other countries planning for a similar transition.

Rural and intercity buses cover longer distances, requiring buses to have longer ranges than those of commercially available BEBs. Range constraints can lead to several challenges, such as a route not being able to be served by standard e-buses, increased costs of fleet conversion to BEBs, as more spare buses may be needed to serve the same route to bridge gaps due to range and charging requirements, reduced operational flexibility compared to diesel buses, increase in idle bus time due to charging, and charging infrastructure installation costs (Zhou et al., 2022). E-bus range limitations can be addressed by recharging BEBs en route using fast opportunity chargers to deliver conventional diesel bus-equivalent operational performance (Kunith et al., 2017). Thus, developing and implementing an appropriate charging infrastructure strategy is crucial to ensuring adequate e-bus range. Charging infrastructure planning includes determining the optimal locations for charging facility installation, the type and number of chargers to be installed at each station, and the optimal BEB charging strategy to minimise infrastructure and operating costs. Optimal distribution of charging infrastructure across the bus route network and a well-planned charging schedule can reduce capital expenditure (CAPEX) on larger batteries and spare buses and, consequently, the lifecycle costs of e-buses. Alternative charging strategies like depot charging systems, opportunity charging, battery swapping, and BEB swapping have been examined in the available literature (Rogge et al., 2018; You et al., 2016; Zeng et al., 2023). However, the literature on BEBs has focused predominantly on urban buses, while research on rural bus networks remains limited.

Charging infrastructure location planning and charging scheduling in rural areas are analytically complex due to numerous possibilities for the charger locations and time intervals for determining the BEB charging schedule, leading to multiple variables and large search spaces. In this context, this study addresses the gap in the literature on integrated charging infrastructure planning and charging scheduling issues in BEB deployment for rural bus networks. We solve a location-allocation problem for the chargers to ensure BEBs can fulfil the existing diesel bus schedule, considering constraints like fleet size, BEB battery capacity, and charger power. A mixed integer linear programming (MILP) optimisation framework is introduced to tackle this problem, considering variations in electricity tariffs throughout the day to minimise infrastructure & charging costs and the prioritisation of stops for effective utilisation through resource sharing. To validate the results generated with the proposed methodology, numerical analysis using the service schedule data on a number of the rural routes served by Kalyana Karnataka Road Transport Corporation (KKRTC) in the state of Karnataka in India, with a fleet size of 281 buses, is carried out.

This study considers key practical considerations reflecting the operation of an actual rural bus network, thereby yielding pragmatic results for bus agencies transitioning from diesel buses to BEBs. The proposed integrated charger planning and scheduling approach aims to effectively reduce operational and strategic costs, leading to optimised decision-making. Overall, the following are the key contributions of this study:

1) Development of an optimisation framework for integrated charging infrastructure planning and charging scheduling for rural bus networks. The essential problem in integrated charging infrastructure planning and charging scheduling for rural bus networks is to simultaneously determine the optimum location and capacity of charging facilities, along with optimal charging schedules for e-buses. This model aims to minimise the costs associated with charging infrastructure and the electricity consumed by the buses, considering time of use (TOU) electricity tariffs.
2) Creation of a methodology for a "priority-based" charger allocation scheme, along with limited bus schedule alterations. The "priority-based allocation" enables more efficient utilisation of the charging infrastructure, reduces peak power demand, and necessitates fewer fast chargers overall. Locations with higher priority are given precedence for installing charging facilities, as they facilitate resource sharing among a greater number of bus routes (explained in more detail in Section 4).
3) Design of a practical solution for a large-scale, complex rural network and evaluation of its efficacy through the KKRTC case study and providing pragmatic results for bus agencies transitioning from diesel buses to BEBs. The model also identifies bus routes that are not viable for electrification due to insufficient dwell times to charge BEBs to a level that enables them to complete their trips.

The rest of this paper is structured as follows: The contributions of previous literature in this field and the studies relevant to this paper are discussed in Section 2. The problem definition, proposed mathematical model formulation, and heuristic algorithm details are presented in Section 3. A case study based on a real-world rural bus network is covered in Section 4. The research results are presented in Section 5. Finally, Section 6 concludes the study and provides directions for further research in this field.

2. Literature review

Significant research has been conducted over the past decade in the domain of BEB planning, including timetabling (Alamatsaz et al., 2022; Teng et al., 2020; Xu et al., 2023), fleet composition and sizing (Rogge et al., 2018; Yıldırım and Yıldız, 2021), vehicle and crew scheduling (Perumal et al., 2021; Sistig and Sauer, 2023; Wang et al., 2022), charging facility planning (Guschinsky et al., 2021; Kunith et al., 2017; Xylia et al., 2017), and charging scheduling (He et al., 2020; Huang et al., 2023; Pettet et al., 2021). Considering the scope of this study, in the domain of charging infrastructure planning and charging scheduling, the following two approaches have been taken in the past: 1) a sequential approach that addresses the two issues separately (He et al., 2018; Uslu and Kaya, 2021; Wu et al., 2021) and 2) an integrated approach (Gairola and Nezamuddin, 2023; Wang et al., 2017; Zhou et al., 2022). This study focuses on the latter approach.

Several researchers have worked on the optimal design of charging infrastructure, which entails specifying the location and number of chargers in the public transport network and has the objective of minimising the total cost of ownership. Xylia and their research team (2017) proposed an MILP framework for determining the charging facility distribution for large-scale urban networks that minimises the total system cost (Xylia et al., 2017). They also compared the price of BEB adoption with that of continued operations with a 100% biodiesel system. Another study (Kunith et al., 2017) included battery capacity decisions in charging infrastructure planning to capture the trade-off between the battery size and number of chargers required under different operational scenarios. In 2018, Liu, Song, & He determined the optimal battery capacity of buses and location & type of fast charging facilities to be deployed in a bus network using a deterministic MILP model. Their research also included the development of a robust optimisation model to incorporate the uncertainty of energy consumption (Liu et al., 2018). In the same year, Rogge and their research team combined BEB scheduling with the planning of fleet size, bus type, and optimal charging infrastructure for a depot charging BEB system to minimise total procurement and operational costs, along with monetised vehicle schedule adjustments (Rogge et al., 2018). This study did not consider opportunity charging, which is inevitable in the case of rural bus transport systems. Wei and other researchers considered space and time-related constraints and provided a strategy for the optimal deployment of BEBs and charging facilities in an existing bus network previously run by diesel or CNG buses without changing the vehicle schedules (Wei et al., 2018). He et al. (2019) included electricity demand charges, which had been overlooked by previous studies, and formulated an MILP model for effective deployment of fast charging facilities, fleet composition, and installation of energy storage equipment that can solve the problem of high demand charges associated with opportunity charging systems (He et al., 2019). In their work, demand charges refers to the expenses incurred based on the highest electricity consumption rate during periods of peak power demand. Lin and their research team introduced a multistage approach for location-capacity planning of plug-in type fast charging infrastructure, which can accommodate increasing future charging demands. In the two stages, power and transport systems were considered simultaneously for global optimisation of the whole charging supply chain (Lin et al., 2019). Usla & Kaya's (2021) study looked at location and capacity planning of opportunity charging facilities for an intercity bus network, considering the waiting time of buses in the queues at the charging facility, using an M/M/1 queueing theory approach (Uslu and Kaya, 2021). Tzamakos et al. (2023) applied a similar model to urban bus networks, incorporating an M/M/1 queueing concept to limit the waiting time, considering charger location decisions based on the goal of serving multiple bus routes (Tzamakos et al., 2023). In 2021, Guschinsky and other researchers simultaneously solved the fleet sizing and charging facility design problems for deploying BEBs to maximise a socio-ecological value representing the proportion of passenger demand satisfied, considering the system cost as a constraint (Guschinsky et al., 2021). Zeng et al. (2023) addressed the combined challenge of charging infrastructure planning and BEB scheduling for an urban transport network with the strategy of bus replacement (Zeng et al., 2023).

Along with charging infrastructure planning, substantial research has also been carried out on optimal charging strategies for fast charging BEB networks, due to such strategies' significant effect on the overall cost of BEB networks that employ opportunity charging. In 2016, Qin and their research team determined the optimal charging thresholds for different fleet sizes, reducing the peak power demand and minimising the total charging cost (Qin et al., 2016). You and other researchers (2016) provided a framework for battery charging scheduling in a battery-switching approach wherein all the BEBs would find an available charged battery when they reached a battery switching station (BSS). A distributed algorithm with dual decomposition was incorporated to solve the scheduling problem for individual battery boxes across the whole timespan. They were, therefore, able to demonstrate efficacy in large-scale scenarios with better computational performance than exact solution methods (You et al., 2016). He et al. (2020) formulated a network model to determine the optimal charging schedule for a fast charging BEB network with a predefined fleet size, bus battery capacity, and bus line schedule, considering the demand charges and TOU electricity tariffs. In addition, smart charging management was employed, reducing demand charges and lowering the overall BEB charging cost (He et al., 2020). Abdelwahed and their research team (2020) addressed the charging scheduling problem with the help of two types of MILP models based on different discretisation approaches, i.e. the discrete time optimisation (DTO) model and discrete event optimisation (DEO) model. A comparative study was conducted between the two, and the DEO model was found to be the more efficient and practically implementable approach (Abelwahed et al., 2020). In 2023, Bao and other researchers formulated an MILP model for solving the typical charging scheduling problem, but a Lagrangian relaxation method, along with a bi-criterion dynamic programming algorithm, was introduced to extract the individual BEB charging schedules and computational time, and results were compared with a commercial solver – Gurobi (Bao et al., 2023).

Integrated planning of charging infrastructure and charging schedules can help identify charger locations that enable charging to be shifted to off-peak or regular hours. It also reduces the peak charging power demand, thus improving grid management. Due to the economic and operational benefits, a few studies have addressed the two problems simultaneously. Wang and their research team (2017) developed a deterministic optimisation model for determining the location and number of fast chargers, along with the charging schedules, for an urban BEB network. However, the study assumed a fixed recharging duration at transit centres, which is not a suitable approach for the rural case (Wang et al., 2017). Similarly, Zhou and other researchers (2022) included BEB battery sizing decisions, integrated charging infrastructure, and the charging scheduling problem for an urban setting in their study, considering real-world factors like weight-based energy consumption. They proposed a deterministic and robust optimisation model to account for the energy consumption uncertainty (Zhou et al., 2022). The scheduling of overnight charging activities at the depots was not included in the scope of the above two studies. Hu and their research team (2022) addressed the integrated charging facility planning and charging scheduling problem through an optimisation framework, including decisions regarding BEB battery capacity and a fine for any delay in the schedule caused by charging. A robust counterpart was proposed to consider the uncertainty in passenger demand. He et al. (2022) proposed a two-phase optimisation model, with the BEB battery capacity, fast charging facility configurations, and charging schedules fixed in the first phase. The second phase entailed the application of a rolling horizon approach to generate real-time charging schedules based on the actual arrival time and BEB state of charge (SOC) data. However, in this study, each charger was assigned to a single bus route, resulting in more chargers, higher peak charging power demand, and inefficient utilisation of charging infrastructure (He et al., 2022).

To deal with this issue, in 2023, Gairola & Nezamuddin formulated a deterministic optimisation model with charging resource sharing among multiple bus routes, providing the optimal choices regarding battery sizes, opportunity charger location, number, and size, and charging schedules for an urban BEB-operated public transport network. A robust counterpart to address energy consumption uncertainty was also presented.

Table 1 summarises all the abovementioned studies based on their scope and the type of problem addressed.

Most related work on integrated charging infrastructure design and charging scheduling has provided solutions for urban public transport networks, where fast charging is done only at terminals or major interchange hubs. However, an approach for electrifying rural bus services has thus far received limited research attention. Rural routes cover greater distances, necessitating charging BEBs at intermediate stops in addition to terminals, thereby increasing the number of potential locations for charging facility installation and adding substantial computational complexity. The solutions of urban BEBs cannot be directly applied to rural routes, as these routes have unique challenges, including sparse and directional demand patterns, limited charging infrastructure availability, and economic viability concerns, especially in developing countries (Jiao et al. 2023). Moreover, as highlighted by Zeng and Qu (2022), there is an uneven flow of passengers and a need for optimal planning of rural BEBs, as well as economic concerns associated with rural BEBs. Similarly, Johari (2023) highlighted the limited availability of charging infrastructure and economic viability concerns for rural BEBs, as most charging infrastructure is concentrated in major cities, making it difficult and costly for rural BEBs. Furthermore, another unique challenge is the consideration of long distances for travel and the use of electric buses. In this direction, Uslu and Kaya (2021) presented a MILP model considering BEB waiting time for the intercity electric bus network. Charging facility installation cost and operating cost, as well as the number of stops for charging, are considered in their model. Similarly, (Xylia et al., 2017) have also considered intercity bus operation for determining optimal charging infrastructure distribution. Apart from

Table 1
Comparative literature review.

j	Scope	Modelling approach	Objective function	Intercity services	Charging decisions			Operational decisions			
					LD	CD	CS	FS	BC	CC	BS
(You et al., 2016)	Battery switching	Dual decomposition	Charging costs	×	×	×	✓	×	×	×	×
(Xylia et al., 2017)	Mixed fleet (biodiesel, biogas, and electric)	MILP	Annualised infrastructure, vehicle, & energy consumption costs	✓	✓	×	×	×	×	×	×
(Kunith et al., 2017)	Energy consumption simulation	MILP	Charging & transformer station installation cost, battery cost	×	✓	×	×	×	✓	×	×
(Wang et al., 2017)	Fixed charging time	MILP	Deadhead costs, recharging waiting costs, charger cost, charging facility installation cost	×	✓	✓	✓	×	×	×	×
(Liu et al., 2018)	Energy consumption uncertainty	MILP	Battery cost, charging facility installation cost	×	✓	✓	×	×	✓	✓	×
(Wei et al., 2018)	Existing bus routes and schedule	MILP	BEB procurement cost, charging facility installation cost	×	✓	✓	×	×	×	×	×
(Rogge et al., 2018)	Depot charging BEB system, no opportunity charging	Grouping genetic algorithm	BEB CAPEX, charger cost, BEB operating and energy cost	×	×	✓	✓	✓	✓	×	✓
(He et al., 2019)	Demand charges	MILP	Battery cost, charging facility, charger, and storage device costs, demand cost	×	✓	✓	×	×	✓	✓	×
(Lin et al., 2019)	Multi-phase approach, future charging demands	Mixed integer second-order cone programming	Fixed and variable costs of charging infrastructure, power grid line construction and power loss costs	×	✓	✓	×	×	×	×	×
(Y. He et al., 2020)	Smart charging management	Network model	Charging costs	×	×	×	✓	×	×	×	×
(Abdelwahed et al., 2020)	DTO & DEO models	MILP	Charging costs	×	×	×	✓	×	×	×	×
(Uslu & Kaya, 2021)	BEB waiting time at charging facility	MILP	Charging facility installation cost and operating cost, number of stops for charging	✓	✓	✓	×	×	×	×	×
(Guschinsky et al., 2021)	Mixed fleet	Heuristic with particle swarm optimisation (PSO)	Total passenger demand	×	✓	✓	×	✓	×	×	✓
(Wu et al., 2021)	Calculation of charging demand and distribution network capacity	Binary PSO algorithm	Construction, operation, travel, and power loss costs	×	✓	✓	×	×	×	×	×
(Wang et al., 2022)	No partial charging	MILP	BEB cost, battery cost, charger cost	×	✓	✓	×	✓	✓	×	✓
(Zhou et al., 2022)	Weight-related energy consumption, energy consumption uncertainty	MILP	Battery cost, charger cost, charging cost	×	✓	✓	✓	×	✓	×	×
(Hu et al., 2022)	Passenger demand uncertainty	MILP	Battery cost, charger cost, charging cost, fine for waiting	×	✓	×	✓	×	✓	×	×
(He et al., 2022)	Rolling horizon method for real-time charging scheduling	MILP	Battery cost, charging facility installation cost, charging cost	×	✓	✓	✓	×	✓	✓	×
(Tzamakos et al., 2023)	BEB waiting time at charging facilities	MILP	Charger cost	×	✓	✓	×	×	×	×	×
(Zeng et al., 2023)	Bus replacement strategy	MILP	BEB cost, charging facility installation cost, passenger loss, passenger crowding, access, and cross-station costs	×	✓	✓	×	×	×	×	✓
(Bao et al., 2023)	Lagrangian relaxation	MILP, bi-criterion dynamic programming	Charging costs	×	×	×	✓	×	×	×	×
(Gairola & Nezamuddin, 2023)	Energy consumption uncertainty	MILP	Battery cost, charging facility installation cost, charger cost, TOU charging cost, demand charges	×	✓	✓	✓	×	✓	✓	×
This study	Priority-based location decisions, infeasible route identification, limited schedule delays	MILP, heuristic algorithm	Charging facility installation cost, charger cost, charging cost	✓	✓	✓	✓	×	×	×	×

LD = location decision, CD = capacity decision, CS = charging scheduling, FS = fleet size, BC = battery capacity, CC = charger capacity, BS = bus scheduling

these concerns, there is also a need for considering TOU electricity tariffs.

Considering these unique challenges, the essential problem for rural bus networks is to have an integrated charging infrastructure planning and charging scheduling, which simultaneously determines the optimum location and capacity of charging facilities, along with optimal charging schedules for e-buses. Accordingly, in our study we address these unique challenges of rural BEBs by minimising planning and operating costs, including the charging station installation cost, charger acquisition cost, and charging cost. Furthermore, there is a need to identify bus routes that are not viable for electrification due to insufficient dwell times to charge BEBs to a level that enables them to complete their trips. Accordingly, this study considers key practical considerations of rural BEBs, thereby yielding pragmatic results for bus agencies transitioning from diesel buses to BEBs. The proposed integrated model aims to reduce operational and strategic costs, leading to optimised and informed decision-making.

3. Methodology

3.1. Problem description

As briefly discussed in Section 1, the aim of this study is to address the problem of rural bus network electrification. A rural BEB network comprises multiple depots, bus routes, and stops, where the bus fleet must complete a predefined daily trip schedule. Depots are equipped with a fixed number of slow chargers (with output power below or equal to 180 kilowatts (kW)), and buses can be charged overnight. The bus dwell time between trips can be used for opportunity charging using fast chargers (with output power equal to or above 240 kW). The BEB battery size, fleet size, charger specifications, and bus schedule are known beforehand. The term charging facility refers to the location or site equipped with the necessary electrical and civil infrastructure to support one or more chargers for electric bus operations. While charger or charger gun refers to the electrical equipment or device that delivers power to the electric bus battery. BEB charging infrastructure planning for such a network involves determining the locations for opportunity charging facilities and the number of fast chargers (Each with one charging connector further referred to as charger gun) to be installed at each selected location. Moreover, the optimal schedule for charging buses at depots or opportunity charging locations is also determined. This schedule includes the charging location, start time, and duration. The values of these decision variables need to be chosen to minimise the total cost, including the fixed cost of power infrastructure deployment at a potential location (selected for opportunity charging), fast charger cost, and daily operating cost (calculated based on TOU electricity tariffs). Fig. 1 illustrates the operation of a bus on a route, showing fixed number of slow chargers at the depot, and opportunity chargers installed at selected stops as an example.

To this end, an optimisation model framework was formulated to design the charging infrastructure and determine the optimal charging schedule to minimise the overall CAPEX and operating costs. There is a definite trade-off between the BEB battery size and number of fast chargers to meet the energy demand, and a sensitivity analysis is therefore needed to determine the most suitable BEB battery size. There may also be some bus routes that are unfeasible to electrify due to the unavailability of adequate dwell time or trip distances exceeding the BEB range. Such bus routes were identified by the model and discounted from further planning, with the assumption that diesel buses would continue to be used on these routes. Along with this, the following assumptions were considered as a part of the problem formulation:

1. The battery consumption rate is linearly proportional to the distance the BEB covers.
2. The battery recharge rate is linearly proportional to the charging time.
3. A homogeneous BEB fleet is considered for each bus route; thus, the battery chemistry, charging and discharging characteristics, and performance are the same for each BEB.
4. The depots are equipped with slow chargers, as overnight charging is possible. However, based on the model's results, stops are selected for fast charging.
5. When the BEB returns to the depot at the end of all the daily trips, the SOC is considered to be equal to the reserve limit.
6. The BEB SOC must remain above the battery reserve limit specified by the battery reserve ratio as a fraction of the entire SOC.

Assumptions 1–3 are applied to simplify the problem and are supported by several studies (Wang et al., 2017, Wang et al., 2022, Gairola and Nezamuddin, 2023). Assumption 1 is realistic as the electric scooter field test conducted by (Yu and Lu, 2013) concludes that relationship between charge consumption and BEB driving distance is almost linear. Assumption 2 is valid as (Hwang et al., 2018) states that recharge rate is proportional to charging duration between 20% and 80% SOC. Assumption 3 is a standard practice as it results in more cost-effective bus schedule. Assumption 4 is logical due to the extended time periods available at the depots for overnight charging compared to the dwell times at the stops between trips, which necessitate faster charging. Assumption 5 is valid because, due to the higher electricity tariffs during peak and regular hours compared to off-peak hours, operators limit opportunity charging to fulfil daily trip requirements, despite having sufficient dwell time for additional charging. Assumption 6 is a general practice to delay battery degradation and improve battery longevity.

The integrated strategic and operational planning framework adopted in this study addresses the limitations inherent in conventional sequential approaches. Planning charging facility locations without considering operational requirements often leads to suboptimal charging schedules, characterized by high peak-hour demand and elevated long-term BEB charging costs. In contrast, a simultaneous decision-making approach enables the identification of charging facility locations that facilitate off-peak charging as much as possible, thereby ensuring more balanced load distribution and cost-efficient system operation.

3.2. Mathematical formulation

A mathematical model was introduced for the charging infrastructure planning and determining the optimal charging schedule. The total operating hours of a day were discretised in time intervals of equal length. The length of the time interval (δ) was chosen based on the desired accuracy and available computational power. Shorter time intervals yield a more accurate charging schedule but also introduce greater complexity into the model. The bus schedule provides information regarding every trip in the form {bus (b), source node (l_s),

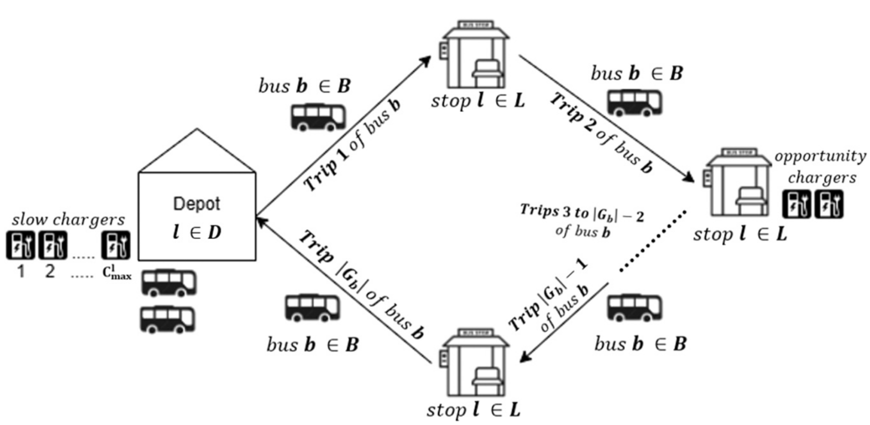


Fig. 1. Problem Description.

destination node (l_e), departure time (t_d), arrival time (t_a), distance (d_{se}), and arrival time of the previous trip of that bus (t_{pa})}, and the model adheres to the schedule. Dwell times cannot be increased for the charging activities. The notations, sets, indices, parameters, and variables are summarised in Table 2.

An MILP model was formulated, as shown below in (1) – (17).

$$Min\ C = \sum_{l \in L} C_f * Z_l + \sum_{l \in L} \sum_{c=1}^{C^l_{max}} C_g * V_{lc} + \sum_{b \in Bl} \sum_{\in L_b} \sum_{c=1}^{C^l_{max}} U * \delta * \left(\sum_{t \in T_n} C_n * Y_{blct} + \sum_{t \in T_p} C_p * Y_{blct} + \sum_{t \in T_o} C_o * Y_{blct} \right) + \sum_{b \in Bi} \sum_{\in \{1, 2, \ldots, |G_b|\}} M * S_{bi} \tag{1}$$

The objective function (1) is the minimisation of the total cost component, comprised of three terms: 1) fixed cost of charging facility installation; 2) procurement cost of fast chargers; and 3) daily BEB charging cost based on TOU electricity tariffs. The final term in the objective function ensures the model's feasibility by addressing situations where electrification of a bus route is not viable due to the unavailability of enough dwell time for charging. In such cases, the decision variable S_{bi} becomes positive. However, the large penalty imposed by the big-M ensures that S_{bi} remains strictly zero when electrification is possible on a given route.

Subject to:

$$\sum_{b \in B_l} \boldsymbol{Y_{blct}} \leq \mathbf{1}, \quad \forall \boldsymbol{l} \in \boldsymbol{L} \cup \boldsymbol{D}, \quad \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, .., \boldsymbol{C^l_{max}}\}, \quad \boldsymbol{t} \in \boldsymbol{T} \tag{2}$$

Table 2
Sets, parameters, and decision variables.

Indices and sets	
$\boldsymbol{L}$	Set of stops indexed by $l \in L$
$\boldsymbol{B}$	Set of buses indexed by $b \in B$
$\boldsymbol{T}$	Set of time intervals indexed by $t \in T$
$\boldsymbol{T_n}$	Set of regular hour time intervals
$\boldsymbol{T_p}$	Set of peak hour time intervals
$\boldsymbol{T_o}$	Set of off-peak hour time intervals
$\boldsymbol{B_l}$	Set of buses that pass from stop $l \in L$
$\boldsymbol{L_b}$	Set of all stops and depots on bus route $b \in B$
$\boldsymbol{D}$	Set of depots
$\boldsymbol{G_b}$	Set of trips of bus $b \in B$ indexed by $i = \{b, l_s, l_e, t_d, t_a, d_{se}, t_{pa}\}$
Parameters	
$\boldsymbol{C_f}$	Fixed cost of installing a charging facility at a stop
$\boldsymbol{C_g}$	Cost of a fast charger
$\boldsymbol{C_n}$	Charging cost during regular hours - 6 am-6 pm (INR/kWh)
$\boldsymbol{C_p}$	Charging cost during peak hours - 6–9 pm (INR/kWh)
$\boldsymbol{C_o}$	Charging cost during off-peak hours - 9 pm-6 am (INR/kWh)
$\boldsymbol{m_{blt}}$	1, if bus b can be charged at location l at time t, otherwise 0
$\boldsymbol{E}$	BEB battery size (kWh)
$\boldsymbol{\gamma}$	Reserve battery ratio
$\boldsymbol{\varepsilon}$	BEB energy efficiency (kWh per km)
$\boldsymbol{R}$	Total range of BEB $= \frac{E * (1 - \gamma)}{\varepsilon}$ (km)
$\boldsymbol{U}$	Charging rate of the charger (kWh per min)
$\boldsymbol{KPM}$	km gain per minute of charging $= \frac{U * R}{E}$ (km per min)
$\boldsymbol{C^l_{max}}$	Maximum number of chargers allowed at stop/depot $l \in L \cup D$
$\boldsymbol{\delta}$	Length of time interval (minutes)
$\boldsymbol{D_b}$	Base depot of bus $b \in B$
$\boldsymbol{M}$	A huge positive number
Decision variables	
$\boldsymbol{Z_l}$	1, if a charging facility is installed at stop $l \in L \cup D$, otherwise 0
$\boldsymbol{Y_{blct}}$	1, if bus $b \in B$ is charged at stop $l \in L_b$ by charger gun c at time-interval $t \in T$, otherwise 0
$\boldsymbol{V_{lc}}$	1, if charger gun c at stop $l \in L \cup D$ is utilised, otherwise 0
$\boldsymbol{S_{bi}}$	Distance by which SOC is inadequate during i^{th} trip of bus $b \in B$
$\boldsymbol{W_{bi}}$	SOC of bus $b \in B$ after its i^{th}trip (km)

Constraint (2) illustrates that only one or no BEB can be charged at a given charging gun at a stop in a specific time interval.

$$\sum_{c=1}^{C^l_{max}} Y_{blct} \leq m_{blt}, \quad \forall b \in B,\ l \in L_b,\ t \in T \tag{3}$$

Constraint (3) ensures that, for a given stop and time interval, the BEBs can be charged only during the dwell times and at a single charging gun.

$$\sum_{b \in B_l} \sum_{t \in T} \boldsymbol{Y_{blct}} \leq |\boldsymbol{B_l}| * |\boldsymbol{T}| * \boldsymbol{V_{lc}}, \quad \forall \boldsymbol{l} \in \boldsymbol{L},\ \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, ..\boldsymbol{C^l_{max}}\} \tag{4}$$

Constraint (4) assigns value 1 to the variable V_{lc} if, at any time, any bus is charged at the stop l and charging gun c.

$$\sum_{c=1}^{C^l_{max}} \boldsymbol{V_{lc}} \leq \boldsymbol{C^l_{max}} * \boldsymbol{Z_l}, \quad \forall\ \boldsymbol{l} \in \boldsymbol{L} \cup \boldsymbol{D} \tag{5}$$

Constraint (5) states that any charger at a stop can only be used for charging if a charging facility is installed at that stop.

$$\boldsymbol{W_{bi}} + \sum_{c=1}^{C^{ls}_{max}} \sum_{t=t_{pa}}^{t_d} \boldsymbol{KPM} * \boldsymbol{\delta} * \boldsymbol{Y_{blct}} - \boldsymbol{d_{bi}} + \boldsymbol{S_{bi}} = \boldsymbol{W_{b\ i+1}}, \quad \forall \boldsymbol{b} \in \boldsymbol{B},\ \boldsymbol{i} \in \{\mathbf{1}, \mathbf{2}, \ldots, |\boldsymbol{G_b}|\} \tag{6}$$

Constraint (6) is the flow constraint that tracks the SOC of a BEB throughout its daily trips. For the trip of a BEB from Stop l to Stop k**,** the SOC at Stop k will be equal to the SOC at Stop l plus the charge received at Stop l, minus the distance between Stops l and k, plus the shortage term in case the bus route becomes unfeasible for electrification at any point in time.

$$\boldsymbol{W_{b0}} = \mathbf{0}, \quad \forall\ \boldsymbol{b} \in \boldsymbol{B} \tag{7}$$

Constraint (7) sets the SOC of each BEB at a value of 0 when it reaches the depot after completing all its daily trips.

$$\boldsymbol{V_{l\ c+1}} \leq \boldsymbol{V_{lc}}, \quad \forall\ \boldsymbol{l} \in \boldsymbol{L} \cup \boldsymbol{D},\ \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, \ldots\ldots, \boldsymbol{C^l_{max}}\} \tag{8}$$

Constraint (8) ensures an ordered allocation of chargers by implying that the charging gun $c+1$ can be used only if charging gun c has been used.

$$\boldsymbol{W_{bi}} + \sum_{c=1}^{C^{ls}_{max}} \sum_{t=t_{pa}}^{t_d} \boldsymbol{KPM} * \boldsymbol{\delta} * \boldsymbol{Y_{blct}} \leq \boldsymbol{R}, \quad \forall \boldsymbol{b} \in \boldsymbol{B},\ \boldsymbol{i} \in \{\mathbf{1}, \mathbf{2}, \ldots, |\boldsymbol{G_b}|\} \tag{9}$$

Constraint (9) limits the charge received at any stop such that the SOC does not exceed the total range of the BEB.

$$\sum_{i \in \{1, 2, \ldots, |G_b|\}} \boldsymbol{S_{bi}} \leq \boldsymbol{M} * (1 - \boldsymbol{Y_{blct}}), \quad \forall \boldsymbol{b} \in \boldsymbol{B},\ \boldsymbol{l} \in \boldsymbol{L_b},\ \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, \ldots\ldots, \boldsymbol{C^l_{max}}\},\ \boldsymbol{t} \in \boldsymbol{T} \tag{10}$$

Constraint (10) discards the unfeasible bus routes from the planning process by not allowing any charging activity on those bus routes.

$$\boldsymbol{V_{lc}} = \mathbf{1}, \quad \forall \boldsymbol{l} \in \boldsymbol{D},\ \boldsymbol{c} \in \{\mathbf{1}, \mathbf{2}, \ldots\ldots, \boldsymbol{C^l_{max}}\} \tag{11}$$

Constraint (11) allocates a fixed number of slow chargers at the depots.

$$\sum_{l \in L_b} \sum_{c=1}^{C^l_{max}} Y_{blct} \leq 1, \quad \forall b \in B,\ t \in T \tag{12}$$

Constraint (12) ensures that any BEB can only be charged at a single charging gun at a particular location.

$$\boldsymbol{W_{bi}} \geq \mathbf{0}, \quad \forall \boldsymbol{b} \in \boldsymbol{B},\ \boldsymbol{i} \in \{\mathbf{1}, \mathbf{2}, \ldots, |\boldsymbol{G_b}|\} \tag{13}$$

$$S_{bi} \geq 0, \quad \forall b \in B, \quad i \in \{1, \quad 2, \ldots, |G_b|\} \tag{14}$$

$$Z_l \quad \in \{0, 1\} \quad , \forall l \in L \cup D \tag{15}$$

$$V_{lc} \in \{0, 1\} \quad , \quad \forall \ l \in L \cup D, \ c \in \{1, \quad 2, \ldots\ldots, \quad C_{max}^l\} \tag{16}$$

$$Y_{blct} \in \{0, 1\}, \ \forall b \in B, \quad l \in L_b, \ t \in T, \ c \in \{1, 2, ., C_{max}^l\} \tag{17}$$

Constraints (13)-(17) define the domain of the decision variables with Constraint (13), ensuring the reachability of BEBs to every stop along their routes.

3.3. Solution algorithm

Rural public transport networks generally involve many buses in operation and numerous potential charging locations, which results in numerous decision variables, making the optimisation model computationally time-consuming, and it is proven to be NP-hard. To deal with this issue, we propose a heuristic algorithm that makes sequential decisions for each bus route.

A bus route is defined as the sequence of trips operated by a BEB during a day, starting and ending at the same depot. Buses are fully charged overnight at the depot using slow chargers, while opportunity charging is performed at intermediate stops as needed. The algorithm iterates over all the bus routes in the ascending order of the departure time of the bus from the depot, checks for the reachability for each trip of that bus route, and allocates chargers at previously visited locations based on a defined logic according to when the reachability constraint is violated during the bus journey. The "priority" of a location is based on the number of bus routes that include it as a stop. In simpler terms, it reflects the number of buses that pass through that stop at least once during their daily journeys. Locations with higher priority are given precedence for installing charging facilities because they facilitate resource sharing among a greater number of bus routes. This strategy enables more efficient utilisation of the charging infrastructure, reduces peak power demand, and necessitates fewer fast chargers overall.

When the reachability condition along a bus route is not met, the algorithm initially attempts to conduct charging activities at existing charging facilities on that bus route, if they were previously allocated during the past iterations of the algorithm. It determines whether the BEB could have been charged sufficiently to complete either all remaining trips or at least the next trip at those locations. If no charging facilities were previously allocated or if the BEB cannot be charged to a sufficient SOC level to complete even the next trip, new chargers are assigned based on a descending order of priority of a stop, as needed. The feasibility of charging the BEB using both the newly allocated and existing chargers is then re-evaluated. If sufficient time still remains unavailable, the bus schedules are delayed by a predetermined threshold duration to extend the charging activities and ensure the electrification of the bus route. This process of allocating chargers is repeated iteratively, employing a greedy strategy to ensure complete electrification of all bus routes. The operator can determine the schedule delay threshold based on the revenue loss per unit of time due to extended dwell times. When the dwell time is extended at any stop for charging activities, all the subsequent trips are also delayed by the same amount of time. The algorithm complies with all the constraints included in the mathematical model. Similar to the optimisation model, we discretised the total timespan of a day into intervals of equal length, and the algorithm assigns charging activities to the time intervals. To simulate actual BEB operations, the system continuously tracks charger status, i.e. whether they are busy or unoccupied, across all time intervals. Initially, depots are equipped with a predetermined number of slow chargers, each set to an "unoccupied" status for all time intervals. As the algorithm iterates over bus routes, additional opportunity chargers are allocated at intermediate stops as needed. When a bus is charged at any charging facility, the status of that charger is updated to "occupied" for the corresponding time interval(s). The algorithm identifies bus routes where electrification is not feasible due to insufficient dwell time between trips to recharge adequately for subsequent trips, even after delaying the schedule up to a specified threshold duration. Bus routes facing such constraints are omitted from the planning process, and consequently, no charging activities are conducted for these routes. Fig. 2 depicts the flow diagramme of the proposed algorithm and describes all the steps involved in the solution methodology.

The priority-based charging facility allocation strategy minimizes the number of chargers by strategically selecting locations that can serve the maximum number of bus routes. This approach closely aligns with the objective of the mathematical model, achieving near-optimal results with significantly lower computational effort. If the bus routes are iterated over in a specific order, the heuristic can potentially yield the same number of opportunity charger allocations as the exact method. However, this optimal order cannot be predetermined. Additionally, when a BEB visits a stop with a charging facility multiple times in a day, the algorithm schedules charging during off-peak hours to minimize daily operational costs. Thus, the proposed algorithm effectively replicates the optimization model, capturing its constraints while emulating the optimal charging facility allocation process with high computational efficiency.

In addition to solving the network-wide charging infrastructure planning and schedule optimisation problem, the robustness of the algorithm has been tested for input data variations using sensitivity analysis. The impact of key input variables like the BEB battery size and power available from opportunity charging is analysed. This analysis tests the robustness of the algorithm for alternative input variables while also providing practical insights on the approach to be adopted towards optimising cost of transition to BEBs.

4. Case study description

To demonstrate and verify the performance of the proposed optimisation model and heuristic algorithm, extensive numerical analysis is presented in this section, carried out on the real-world KKRTC bus network, which provides rural public bus services in Karnataka, India. The network is currently served exclusively by diesel buses, but the planning for fleet electrification is underway. The route-wise fleet allocated, route length, list of stops, and schedule data of current services were obtained from the KKRTC and used as inputs to the charging infrastructure planning model. Given the fleet size, battery size, charger capacity, and bus schedule, the model determined the optimal location of charging facilities, the number of chargers at each charging facility, and a BEB charging schedule that minimises the CAPEX and charging costs.

A small-scale subsection of the overall KKRTC bus network, including five depots of the 'Yadgiri' division with 100 buses each and 281 bus routes operating from these depots, was selected to implement the numerical study. There are 106 intermediate stops, which could be potential locations for opportunity charging facilities. The network comprises 1225 bus trips with an average route length of 81.3 km. Each bus performs roughly 4–5 trips daily, on average. According to KKRTC's current plan to install one charger for every four buses, each of the five depots was considered to be equipped with 25 slow overnight chargers. The BEBs can be charged at their respective depots using these slow chargers once they reach the depot after completing their daily trips and before they depart, as per their schedule for the following day. For modelling, the total timespan of a day was divided into 5-minute time intervals.

The input values of the cost parameters, BEB and charger specifications are presented in Table 3. These input values were identified based on market consultations and Government notifications to meet the research objective of providing practical decision making support to rural bus agencies. All network-related parameters are sourced from secondary data provided by KKRTC, while charger-related parameters,

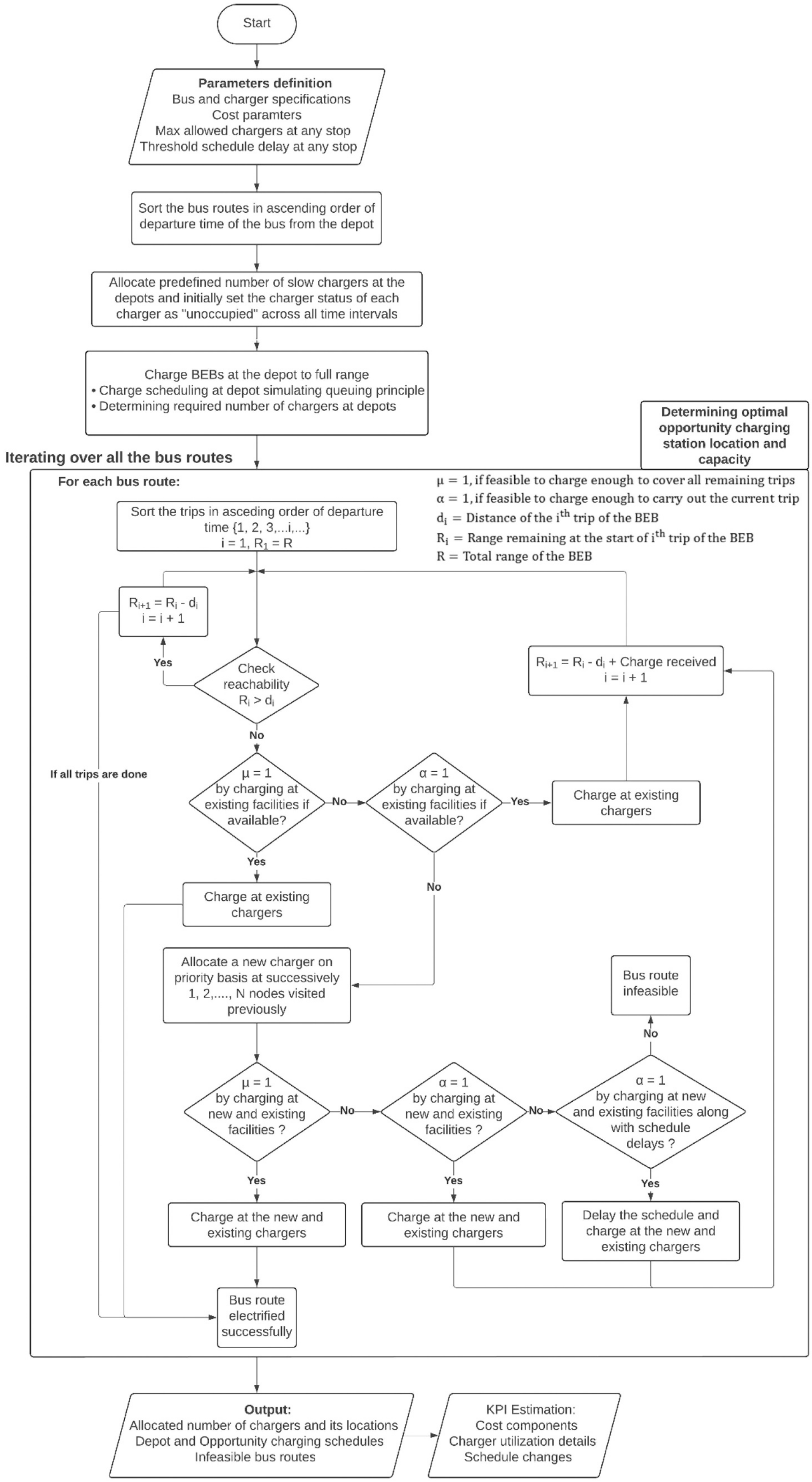


Fig. 2. Flow diagramme of proposed heuristic algorithm.

Table 3
Cost and bus network parameters[*].

Cost parameters	Amount in INR
Fixed cost of installing a charging facility at depot $l \in D$, C_f^l	50,000,000 ~(560000 USD)
Fixed cost of installing a charging facility at any stop $l \in L$, C_f^l	30,000,000~(338000 USD)
Cost of a fast charger, C_g	1800,000 ~(20000 USD)
Charging cost during regular hours – 6 am-6 pm (INR/kWh), C_n	6
Charging cost during peak hours – 6–9 pm (INR/kWh), C_p	7.5
Charging cost during off-peak hours – 9 pm-6 am (INR/kWh), C_o	4.5
Other parameters	Value
BEB battery size (kWh), E	320
Reserve battery ratio, γ	0.2
BEB energy efficiency (kWh per km), ε	1.1
Charging rate of fast charger (kWh per min), U_l for $l \in L$	2.6
Charging rate of slow charger (kWh per min), U_l for $l \in D$	1.2375
Maximum number of chargers allowed at any stop $l \in L$, $C_{\max}^l$	4
Maximum number of chargers allowed at depot $l \in D$, $C_{\max}^l$	25
Length of time interval (minutes), δ	5

[*]-Inputs from secondary data and stakeholder consultations, 1 USD = INR 88)

including the fixed cost of installing a charging facility at the depots and fast chargers at opportunity charging locations, were provided by potential Original Equipment Manufacturers (OEMs) supplying buses and chargers to KKRTC. The electricity costs were estimated based on the latest tariff order published by the Karnataka Electricity Regulatory Commission (KERC). KKRTC could potentially choose from three BEB models on the Indian market at the time of conducting the study, each with varying battery capacities: 250 kilowatt-hours (kWh), 320 kWh, and 395 kWh. The fast chargers, available for KKRTC now offer power ratings ranging from 150 kilowatts (kW) to 600 kW. For the purposes of this study, we present a scenario where a BEB battery size of 320 kWh is chosen and a charger power of 240 kW with a charging rate of ~2.6 kWh per minute, the most common charger capacity in India in recent years was selected for analysis. The charging rate of overnight slow chargers is assumed to be half that of fast chargers based on the current configuration of chargers used in India. Moreover, in rural areas in Karnataka, the regulations cap charging facility capacity to be 1 megawatt (MW) for opportunity charging stops and 5.5 MW at any depot. Thus, the maximum number of chargers allowed at any opportunity charging stop is restricted to four to meet the 1 MW cap with 240 kW chargers. The model was executed using these inputs based on which the results presented in the subsequent sections were derived. All costs are reported in Indian Rupees (INR), with an approximate conversion rate of 1 USD = INR 88 (as of 2025) for reference.

5. Results

5.1. Mathematical model results

Commercial solver Gurobi version 9.5.2 was used to solve the mathematical model. All the experiments were implemented using the Python programming language, and the computations were performed using a 64-bit Windows 11 desktop with an Advanced Micro Devices (AMD) Ryzen 7 7745HX central processing unit (CPU), a 3.60 gigahertz (GHz) processor, and 16 gigabytes (GB) of random access memory (RAM). The mathematical model comprises 19,63,515 decision variables, including 19,61,116 binary and 2399 continuous variables. The optimal results were achieved within a computation time of 6292.54 s, with a 0.00% gap observed between the incumbent solution and the best bound.

Table 4 shows the optimal value of the objective function and individual cost components. Note that the number of chargers at the depots is fixed. Hence, the cost of slow chargers installed at the depot and the charging facility installation costs (at the depot) are excluded from the objective function, as they are not subject to optimisation. Cost components 1 and 2 pertain to strategic planning considerations, whereas component 3 represents the daily charging cost. It should be noted that cost components 1 and 2 are mainly used for determining the location and capacity, while cost component 3 is based on the daily usage charging cost. It makes it rational to consider daily charging costs, as opposed to annual, to determine the optimal charging schedule.

A set of bus routes in the Yadgiri division and the optimal charging facility locations are marked on the map in Fig. 3. The color of each point, as indicated in the legend, represents the capacity of the proposed charging facility at that location. The locations determined for charging facilities are at the intersection of roughly 33 bus routes on average and a median of 17 bus routes, thus ensuring efficient charger utilisation through resource sharing. More chargers are allocated at higher-priority locations, which aligns with the desirable characteristics of charging facility distribution. Higher-priority locations are anticipated to be close to large urban areas, which facilitates charging facility installation thanks to grid connectivity and quick access to other utilities.

Fig. 4 illustrates BEB SOC variation throughout the day along all the 170 successfully electrified bus routes, represented in terms of the remaining km range, alongside TOU-based electricity costs (INR/kWh), represented by the blue dotted line. The increase and decrease in SOC level depict BEB charging and discharging, respectively. BEBs are primarily charged at the depot during off-peak hours. During the day, opportunity charging is strategically conducted to enable BEBs to fulfil the remaining daily trips while also optimising charging costs by accommodating charging during off-peak hours. Moreover, by charging fully at the depot, the required number of opportunity chargers decreases, reducing optimal infrastructure costs.

Unlike previous literature, in which BEBs were assumed to begin their journey fully charged, this study relaxes this assumption. As a result, the charging schedule of BEBs at the depot is determined using the proposed framework. On average, the BEBs are charged using opportunity chargers for 26.886 min throughout the day. The BEBs are charged at intermediate stops only during dwell time to avoid delays in the existing bus schedule. Thus, a total of 111 bus routes out of 281 analysed became infeasible for electrification; 86 of them included at least one trip that was longer than the maximum BEB range, and the remaining 25 could not be electrified due to a lack of sufficient dwell times in between trips. This resulted in the successful electrification of 60.498% of the bus routes, i.e. 170 out of 281 bus routes in the Yadgiri division.

Fig. 5 depicts the chargers' occupied and vacant states throughout the day. Fig. 5(a) shows the opportunity chargers' status, while the status of slow chargers at the Yadgiri depot is represented in Fig. 5(b), to give a better understanding of the charging profile at the depots. In the chart, yellow represents non-charging periods, whereas red indicates periods of charging. It is evident from Fig. 5 that opportunity chargers are used during BEBs' operational hours, while slow chargers at the depots are used during off-peak hours. The average charger utilisation is 19.44%, meaning that the chargers are idle during the rest of the day. Fig. 6 shows the percentage utilisation of individual opportunity chargers throughout the day. It is observed that some chargers exhibit utilization

Table 4
Cost components.

Sr. No.	Cost component	Value (INR 10^7)
1	Total fixed cost of charging facility installation	45
2	Total fast charger acquisition cost	4.68
3	Charging cost per day	0.03175
4	Total cost (including per day charging cost)	49.711

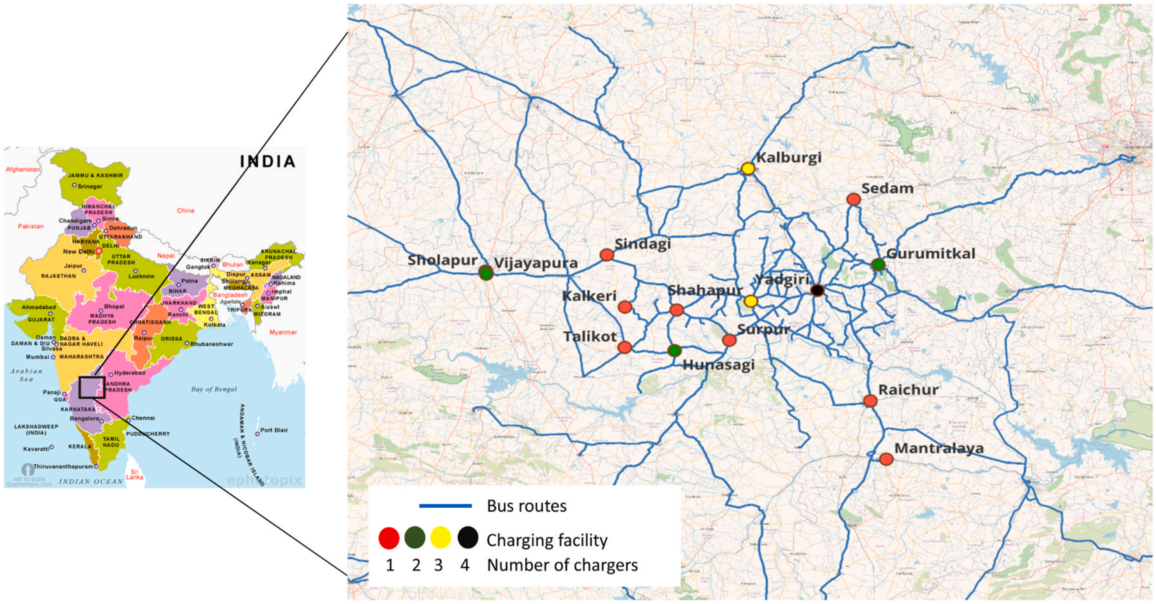


Fig. 3. Yadgiri network and charging facility locations.

levels below 40%. Such underutilization can be mitigated by deploying BEBs with larger battery capacities on routes that include these charging stops. By doing so, the need for intermediate charging at low-demand locations can be eliminated, thereby reducing infrastructure investment, charger gun requirements, and long-term maintenance and operational costs. Although this approach entails a marginal increase in the vehicle cost, it offers a more cost-effective and sustainable solution over the system's lifetime by enhancing overall charging network efficiency.

Fig. 7 depicts the amount of charge received by BEBs during each time interval throughout the day with orange colour bars, alongside the TOU-based electricity cost during that time interval represented by blue dotted line. With 5-minute intervals, there is a total of $(24*60)/5 = 288$ time intervals per day. From this figure, one can see that significant charging is performed during the off-peak hours when the tariffs are much lower, thus optimising the total charging cost.

Next, the results obtained through the algorithm are presented and compared with the results of the optimisation model to assess the usefulness of the proposed algorithm. The proposed heuristic algorithm was implemented using the same input bus schedule data from the Yadgiri division and the parameter values mentioned in Table 3. The algorithm identified the exact same locations for opportunity charging installation; however, the total number of chargers was 31 in the case of the algorithm, whereas it was 26 in the optimisation model for nearly the same level of bus route electrification. Furthermore, the daily charging costs amount to Indian Rupee (INR) 345,780, which is 8.91% higher than the cost calculated by the model. However, the total computing time of the algorithm was just 10.82 s, which is much lower than the 6292.54 seconds taken by the optimisation model. The algorithm would therefore be more effective when dealing with large-scale public transport networks, as it could generate a reliable solution in a finite time, whereas the model would become computationally unsolvable.

If ten minutes of schedule delay is permitted at all intermediate stops, the algorithm allocates a total of thirty opportunity chargers at the exact same fifteen locations (see Fig. 5), but seven more bus routes could be successfully electrified, leading to the electrification of 62.63% bus routes. The charging cost for this scenario is INR 362,346, which is 14.12% higher than the optimisation model. If the schedule is altered to perform additional charging at any stop, the departure time of all subsequent trips is delayed by the same amount of time as the additional time used for charging, keeping the dwell times unchanged as per the existing schedule. In this case, the schedules of 10 bus routes are delayed by 11 min, on average. As evident from the above results, by allowing limited schedule delays, a greater level of network electrification can be achieved with a relatively lower number of opportunity chargers.

To assess the effectiveness of the heuristic algorithm, various sections of the KKRTC network with different scales - ranging from a single depot to an entire division - were extracted. The optimisation model and heuristic algorithm were used to obtain results for these sections. The outcomes of both methods are presented in Table 5. The table shows that the algorithm and optimisation model provide similar results for a small-scale network around the Vijayapura depot. The algorithm allocates five chargers and electrifies nineteen of the total 22 bus routes, while the optimisation model allocates seven chargers and electrifies twenty bus routes. The four locations selected for opportunity charging are the same in both cases. However, as the bus network scale increases, the number of locations selected for opportunity charging remains the same, but, due to the algorithm's opportunistic nature and sequential approach, the number of opportunity chargers allocated is slightly higher than in the model. The algorithm takes substantially less computing time than the model in these cases. For the Kalburgi division, the network was so large that the optimisation model got overwhelmed with decision variables and became computationally unsolvable. The optimisation model could not provide results even after running it for 48 h, while the algorithm provided a satisfactory solution in just 37.94 s. Sometimes, service providers are not looking for the most optimal solution, but rather require an initial feasible solution that can be further improved through inputs from experienced personnel and manual efforts. The optimisation framework requires extremely high computing power to provide results in a finite time, which is not generally available with public transport operators. The heuristic method is an effective alternative when dealing with large-scale rural networks and can help operators obtain an initial solution for charging infrastructure planning and charging scheduling.

5.2. *Sensitivity analysis*

A sensitivity analysis was conducted to study the impact of change in the values of two significant parameters – BEB battery size and opportunity charger power – on the total cost, number of opportunity chargers, and locations selected for opportunity charging. The analysis allows testing the robustness of the algorithm for alternative input values and provided practical inputs for decision making. Generally,

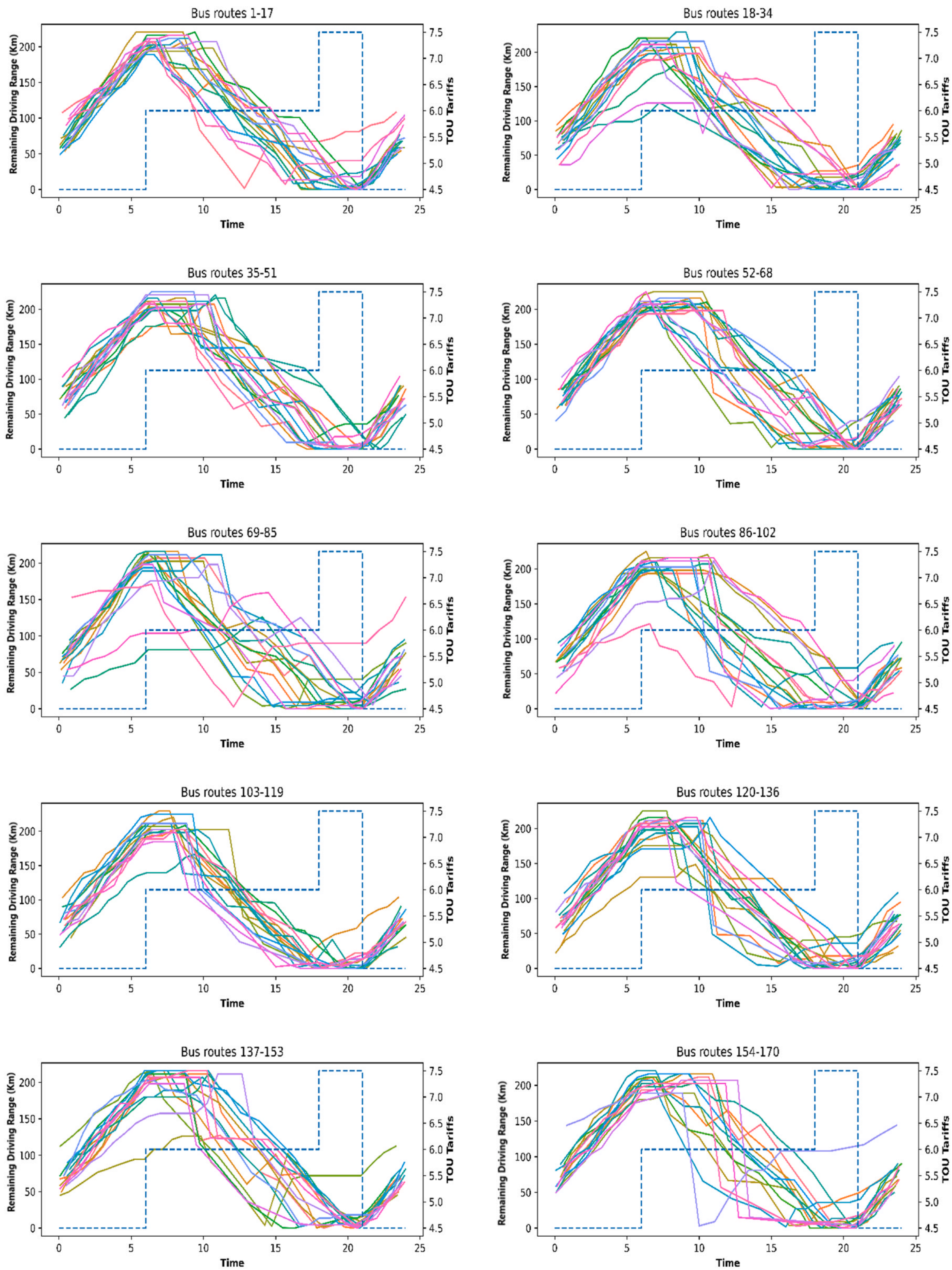


Fig. 4. BEB State of Charge variation (with Each curve shows the Remaining Driving Range of a BEB (in Kms) operating on one of the 170 bus routes; Blue dotted line represents Time of Use (TOU) tariffs.

there is a trade-off between the battery size and number of opportunity chargers required. A lower battery capacity is needed when using an opportunity charging approach than in the case of a depot charging system. Therefore, an opportunity charging approach may result in faster charging and a higher passenger capacity. On the other hand, a larger battery size results in a lower opportunity charging requirement, and a greater level of electrification can be achieved. However, the electricity consumption rate increases due to the increased weight of the BEB. Furthermore, the BEB cost is higher for models with larger batteries, but the daily charging costs are lower since the need for on-route opportunity charging is reduced. Thus, the battery size should be selected carefully, as opting for a very large battery may result in inefficient resource utilisation and higher costs. A larger BEB battery is beneficial if, over time, the additional CAPEX associated with buying a

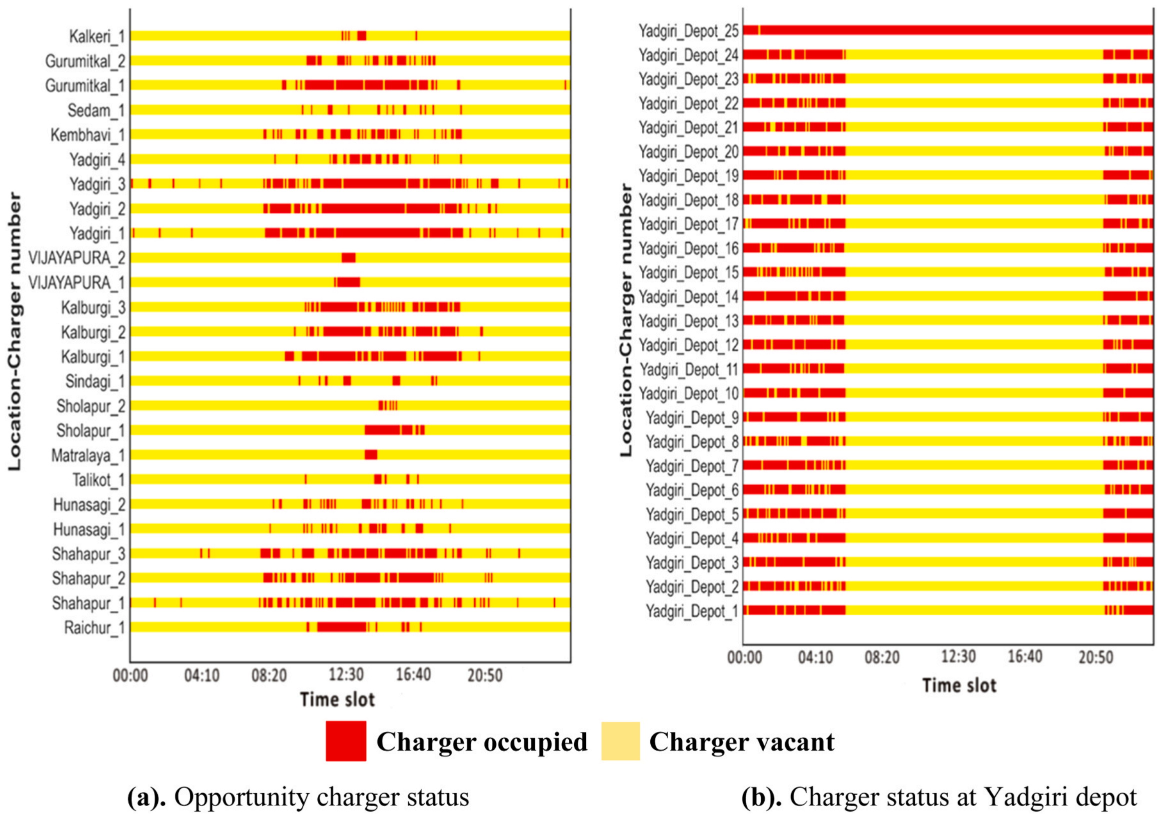


Fig. 5. Charging Status with location-charger number, **(a).** Opportunity charger status, **(b).** Charger status at Yadgiri depot.

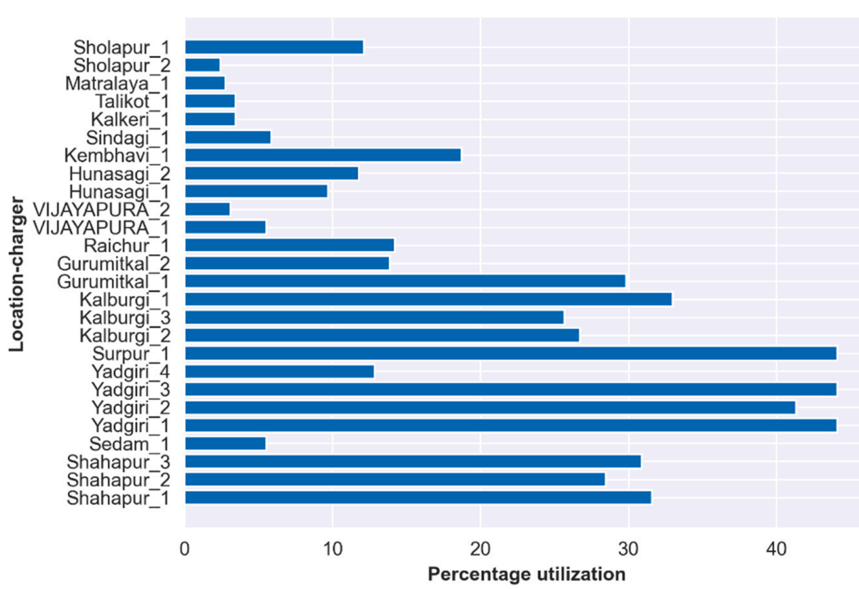


Fig. 6. Percentage utilisation of opportunity chargers.

higher capacity BEB is lower than the savings in charging facility CAPEX and TOU-based charging costs. In this cost comparison, one must consider various factors like the lifespan of BEBs and fast chargers, battery degradation, and increasing future passenger demands. Deploying BEBs with smaller batteries results in the need for more opportunity chargers and increased on-route opportunity charging, resulting in higher charging facility CAPEX and charging costs. Fast charging, in turn, is one of the reasons for excess heat generation in batteries; the lower capacity batteries need frequent charging, leading to speedier battery degradation and reducing battery life. Moreover, due to the reduced BEB range, a smaller proportion of bus routes can be electrified. At the same time, the BEB electricity consumption rate is reduced because the BEBs weigh less.

Similar to the BEB battery size, the charger power also significantly impacts the number of opportunity chargers required and, thus, the total required charging infrastructure and associated costs. Higher charger power leads to quicker BEB charging. Therefore, to achieve the same level of electrification of the bus network, fewer on-route opportunity

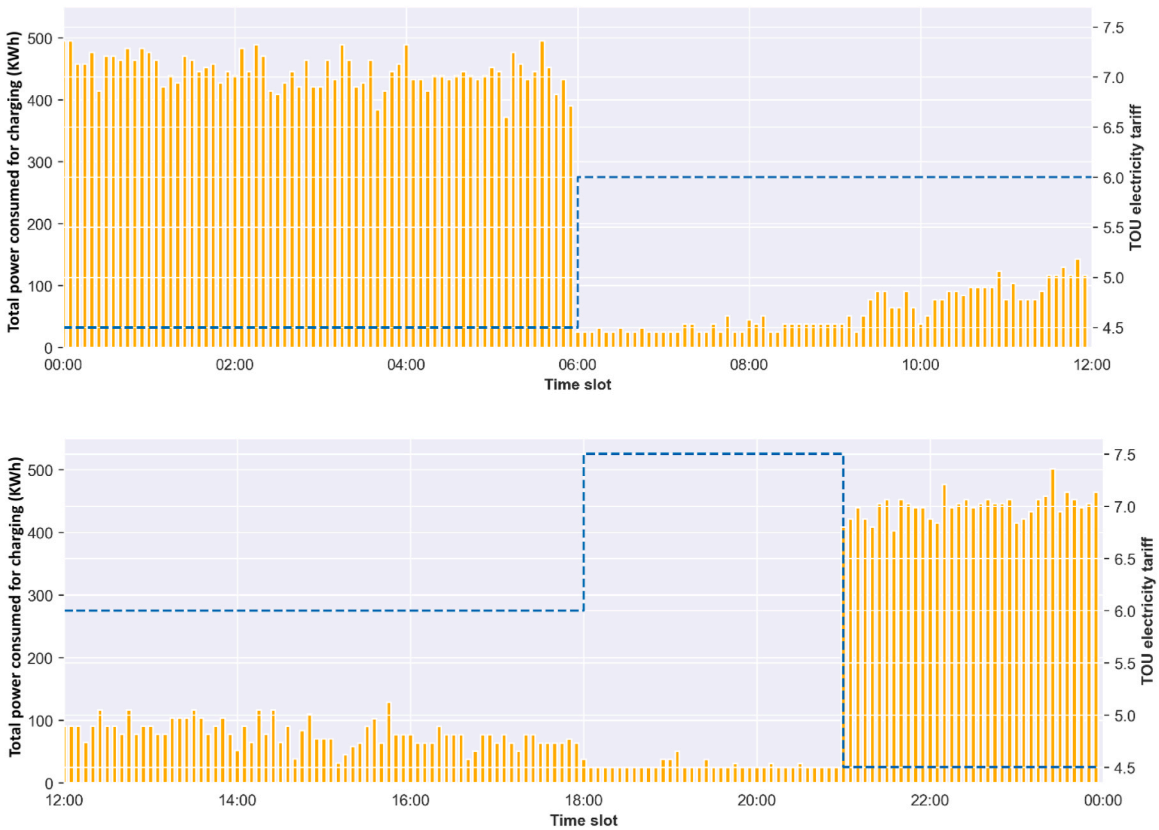


Fig. 7. Charge received in each time interval.

Table 5
Comparison of model and algorithm results.

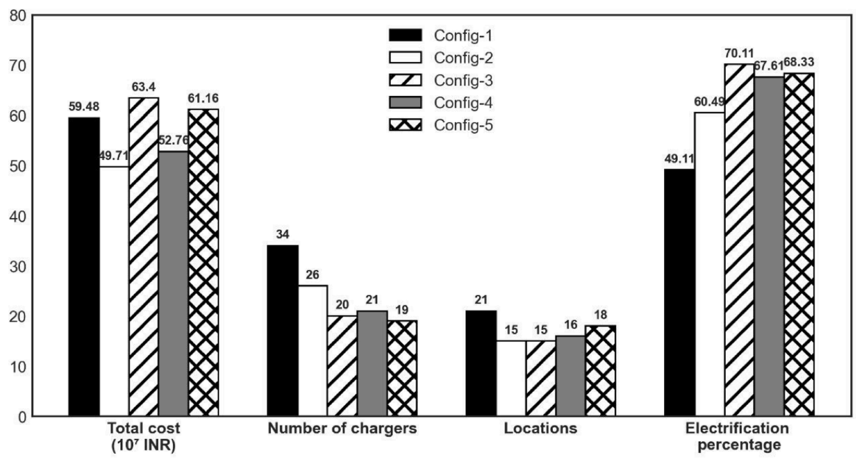
Bus network	Model results					Heuristic algorithm results				
	A	B	C	D	E	A	B	C	D	E
Vijayapura (1 depot, 22 bus routes)	7	4	90.90%	13.26	48.45	5	4	86.36%	1.78	12.90
Ballari (3 depots, 237 bus routes)	15	10	55.27%	722.83	32.72	21	15	54.01%	7.32	48.80
Yadgiri (5 depots, 281 bus routes)	26	15	60.49%	6292.54	49.71	31	15	60.14%	10.82	50.61
Kalburgi (11 depots, 887 bus routes)	-	-	-	-	-	82	52	67.08%	27.38	170.86
All 4 (20 depots, 1427 bus routes)	-	-	-	-	-	130	85	62.29%	45.08	280.02

Note: A = number of opportunity chargers, B = number of selected opportunity charger locations, C = percentage of bus routes successfully electrified, D = runtime, E = objective function value

chargers are required; in other words, a greater level of electrification can be achieved with the same number of chargers. With higher power chargers, the bus network can be operated with BEBs with smaller batteries, as more charging can be accommodated at charging facilities due to reduced charging times. However, high charging power leads to a significant increase in peak load power demands, resulting in high demand charges. Furthermore, charging the BEBs with high power fast chargers causes heat generation, reducing battery life. Typically, there is a cap on the maximum capacity of a charging facility at any given stop, set at 1 MW in this study. Consequently, employing high power chargers reduces the maximum number of opportunity chargers installed at a charging facility. The decisions regarding battery size and charger power are highly interconnected; a combination must be selected that results in the least total cost in the long run, considering all the influencing factors.

Fig. 8 illustrates the impact of battery size and charger power on various model results for five different configurations. The battery size can be 250, 320, or 395 kWh, while the charger power can be 240, 300, or 500 kW. The CAPEX per additional kWh of battery is estimated to be INR 10,000 per kWh (UITP, 2020). For the comparison, a 320 kWh battery was considered as the base case, and when the capacity was increased or decreased, the cost difference was added or subtracted from the total cost, respectively. The charger cost is considered linearly related to its power rating, and thus, the costs for the 240, 300, and 500 kW chargers are estimated to be INR 1.8, 2.25, and 3.75 million, respectively. As seen in Fig. 8, as the battery size increases, the number of opportunity chargers decreases, and the percentage electrification of the bus network goes up. With high power chargers, the bus networks' electrification percentage also increases significantly. For example, with a 300 kW charger, it can be seen in the figure that 21 chargers are required, compared to 26 chargers in the case of a 240 kW charger, and the percentage of electrification increases to 67.61%, up from 60.49% with 240 kW chargers. Thus, the results are consistent with the discussion.

Moreover, with 500 kW chargers, a much higher electrification rate (68.33%) can be achieved with just 19 chargers, a much lower figure than the 26 units needed in the case of 240 kW chargers; still, due to the high charger CAPEX, the total cost is relatively high with 500 kW chargers. Again, the total cost comparison here may be deceptive, and proper analysis requires a comparison of annualised cost values.



Configuration 1: E = 250 kWh, U = 2.6 kWh per minute (240 kW charger)
Configuration 2: E = 320 kWh, U = 2.6 kWh per minute (240 kW charger)
Configuration 3: E = 395 kWh, U = 2.6 kWh per minute (240 kW charger)
Configuration 4: E = 320 kWh, U = 5 kWh per minute (300 kW charger)
Configuration 5: E = 320 kWh, U = 8.3 kWh per minute (500 kW charger)

Fig. 8. Impact of battey and charging speed on fleet electrification.

However, for the sake of comparison of CAPEX, the results presented here are consistent with the actual scenario. Performing such a sensitivity analysis can be beneficial to public transport operators when making critical decisions about bus network design, as it can help them achieve optimal strategic and operating cost outcomes.

5.3. Discussion

From the results, it can be seen that the required number of opportunity chargers steadily rises with an increase in network size. However, this relationship is not strictly linear. For instance, when the analysis is carried out for a combined network, i.e. with all four subnetworks together, the total number of opportunity chargers is lower than the sum of all individual scenarios (refer to Table 5 for more details).

The potential reason for such a decrease is that the network-wide approach first determines the commonality of a given stop within the entire network and then assigns the chargers accordingly. Such an approach can also be beneficial in phase-wise electrification. As optimal locations and capacities for charging facilities for the entire network are determined a priori, rather than first prioritising individual bus routes for electrification and then planning charging infrastructure, sub-optimality is achieved. In the case of limited resources, phase-wise deployment of charging infrastructure, along with targeting certain bus routes, could be an effective alternative strategy. As per the proposed solution approach, a small subset of BEB routes could not be electrified under the considered battery capacity and charging power configurations. In the short term, these routes may continue to be served by conventional diesel or hybrid buses, while alternative solutions such as higher-capacity batteries, faster chargers or emerging zero-emission technologies such as hydrogen fuel cell buses can be evaluated for future phase wise deployment.

Column C in Table 5 shows the percentage of feasible routes within the considered rural network that were electrified using the strategy adopted in this analysis. Our results can help accelerate BEB transition efforts, as we have shown that larger battery sizes, higher charging power, and the allowance of schedule delays can help achieve this. However, schedule delays should be limited to a certain threshold to avoid revenue loss due to reduced operational hours. This threshold can be determined by considering the feasibility of crew scheduling, particularly constraints on drivers' total working hours, and should be supported by simulation studies that evaluate passenger waiting times, service quality levels, queueing effects at charging locations and public response to en-route breaks. The appropriate value may also depend on the availability of alternative buses serving the same destination within the extended time window, which passengers may choose instead of waiting through the delay period. Furthermore, BEBs with larger batteries can be deployed specifically for bus routes with trip distances exceeding the maximum BEB range, instead of opting for a homogeneous BEB fleet. The sensitivity analysis presented in Section 5.2 shows that when larger batteries are used (Configuration 3), the total cost rises significantly compared to Configuration 2, along with a relatively high increase in electrification level. In contrast, when a higher charging power is used (Configuration 4), the total cost increases slightly compared to Configuration 2, with a comparable level of electrification to that of Configuration 3. However, using high power chargers increases the load on the grid, causing higher demand charges. From this discussion, it can be concluded that when the target is only to achieve a higher level of electrification, BEBs with larger batteries should be used. However, if budget is a significant constraint, a slightly higher charging power can prove beneficial in achieving a comparable level of electrification. Furthermore, the savings in total cost of ownership (TCO) per km when replacing a diesel bus with a BEB is INR 5 per km (UITP, 2020). In our study, 170 bus routes were electrified, accounting for a total of 51, 066 bus km. Considering a BEB life of 12 years and 350 total annual days of operation, this results in a total savings of INR 1072.386 million over the entire lifespan of these BEBs, which is 10% of the TCO.

The study results also indicate that employing a hybrid charging strategy in the case of rural BEB systems is beneficial. This includes overnight charging at depots and opportunity charging at intermediate stops along the route. Such a hybrid strategy enables the use of smaller BEB batteries than with a depot charging strategy. This further decreases the total operating cost and enhances BEB utilisation by eliminating deadhead trips to depots for charging.

Efforts have been made to make the solution algorithm realistic and practical. In line with previous studies, the model strikes a delicate balance between realistic considerations and necessary assumptions. Peak charging demand management was incorporated into this study, along with total cost minimisation. The cost of installing a new charging facility dominates the total fast charger cost, leading to a preference for fewer opportunity charging facilities and a greater number of chargers at each facility. This may result in lower CAPEX but higher demand charges. We have incorporated the effect of demand charges into the analysis by limiting the maximum number of chargers per station, keeping peak power demand below a predetermined threshold and restricting the demand charges. Moreover, unlike previous studies that did not identify or manually eliminate bus routes deemed infeasible for electrification from the outset, the proposed model was able to identify such routes, allowing for a more comprehensive evaluation.

6. Conclusion

This study dealt with the issue of charging infrastructure planning and charging scheduling for BEBs in rural areas. We attempted to address the lack of research on rural bus networks by examining the key elements of an existing bus network to generate reliable results. We created an MILP mathematical model with the aim of minimising both the fixed and variable costs associated with charging infrastructure, taking into account TOU-based charging costs. The model determined the most efficient locations and sizes of charging facilities in the KKRTC network and produced comprehensive schedules for BEB charging, favouring periods of low demand. The case study results demonstrate that implementing an integrated approach is effective in decreasing the operational expenses for fleet operators. Even though the model has been demonstrated for one case study, the solution algorithm considers typical input variables such as routes, stops, scheduling constraints, BEB and charging infrastructure parameters which are globally relevant across other bus agencies. Hence, the study advances the state of the art on the topic by presenting a generalized approach to plan for charging infrastructure and charging scheduling.

We introduced a novel solution methodology that uses a sequential approach to identify charger locations and assessed its effectiveness for large networks, considering the prioritisation of stops for effective utilisation through resource sharing. For the considered case of the complex KKRTC bus network (comprising 281 bus routes, five depots, and 106 stops), the solution algorithm provided optimal results. Our solution methodology was found to be scalable and flexible, based on tests run on networks of varying sizes. As the network size increased, the heuristic algorithm significantly reduced computation time, making it more suitable for large networks, where the optimisation model becomes computationally infeasible.

Furthermore, we conducted a sensitivity analysis to determine the impact of BEB battery capacity and fast charger power on different outcomes. The analysis revealed a correlation between the BEB battery size and charger power and a clear trade-off between these two factors. The results of the sensitivity analysis can assist operators in identifying the most favourable values for the BEB battery size and charger power during the planning phase. Therefore, the proposed framework can be beneficial for operators in developing strategies for converting fleets to BEBs and can aid in efficient planning.

Future research in this domain could include demand charges in the objective function. Demand charges have been considered as the expenses incurred based on the highest electricity consumption rate during periods of peak power demand. These charges are influenced by the number of BEBs being charged simultaneously at a specific location. In addition, the assumption of a homogeneous bus fleet could be relaxed to develop a demand-based fleet composition with lower costs. Additionally, establishing the cost impact of environmental factors such as terrain, weather etc. on rural e-bus operations can provide a more comprehensive understanding of the cost implications of alternative technology scenarios and maybe taken up for a more informed study assessment. Furthermore, the optimisation model currently assumes constant values for energy efficiency even though aspects like battery degradation, terrain, weather etc. lead to significant uncertainty in energy consumption. Future studies could improve robustness of the model, by incorporating energy consumption simulations within the cost of operations. BEB battery degradation and a non-linear charging profile could also be considered to improve real-world representativeness of the model. However, integrating these aspects into the analysis is challenging, as this would make the model computationally complex and might require enormous computational power. Nevertheless, such an approach could potentially support highly accurate and cost-effective planning of BEB systems.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Given his role as Editor-in-Chief, Oded Cats had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdelwahed, A., van den Berg, P.L., Brandt, T., Collins, J., Ketter, W., 2020. Evaluating and optimizing opportunity fast-charging schedules in transit battery electric bus networks. Transp. Sci. 54 (6), 1601–1615. https://doi.org/10.1287/trsc.2020.0982.

Alamatsaz, K., Hussain, S., Lai, C., Eicker, U., 2022. Electric Bus Scheduling and Timetabling, Fast Charging Infrastructure Planning, and Their Impact on the Grid: A Review. In: Energies, 15. MDPI. https://doi.org/10.3390/en15217919.

Bao, Z., Li, J., Bai, X., Xie, C., Chen, Z., Xu, M., Shang, W.L., Li, H., 2023. An optimal charging scheduling model and algorithm for electric buses. Appl. Energy 332. https://doi.org/10.1016/j.apenergy.2022.120512.

BloombergNEF (BNEF). (2024). Electric Vehicle Outlook. *BloombergNEF. EVO Report 2024 | BloombergNEF | Bloomberg Finance LP (bnef.com).*

Gadepalli, R., Dhok, D., Nandy, R. & Bhamidipati, S. (2022b). Planning for electrification of rural and intercity buses- Strategies for route, depot and charging location selection. Knowledge brief by *International Association of Public Transport* (UITP). Knowledge-Brief-Route-and-Depot-selection-for-long-range-buses.pdf (uitp.org).

Gadepalli, R., Gumireddy, S., & Bansal, P. (2022a). Cost Drivers of Electric Bus Contracts: Analysis of 33 Indian Cities. *Transportation Research Record.*

Gairola, P., Nezamuddin, N., 2023. Optimization framework for integrated battery electric bus planning and charging scheduling. Transp. Res. Part D Transp. Environ. 118. https://doi.org/10.1016/j.trd.2023.103697.

Guschinsky, N., Kovalyov, M.Y., Rozin, B., Brauner, N., 2021. Fleet and charging infrastructure decisions for fast-charging city electric bus service. Comput. Oper. Res. 135, 105449. https://doi.org/10.1016/j.cor.2021.105449.

He, Y., Liu, Z., Song, Z., 2020. Optimal charging scheduling and management for a fast-charging battery electric bus system. Transp. Res. Part E Logist. Transp. Rev. 142. https://doi.org/10.1016/j.tre.2020.102056.

He, Y., Liu, Z., Song, Z., 2022. Integrated charging infrastructure planning and charging scheduling for battery electric bus systems. Transp. Res. Part D Transp. Environ. 111. https://doi.org/10.1016/j.trd.2022.103437.

He, Y., Song, Z., Liu, Z., 2019. Fast-charging station deployment for battery electric bus systems considering electricity demand charges. Sustain. Cities Soc. 48. https://doi.org/10.1016/j.scs.2019.101530.

He, J., Yang, H., Tang, T.Q., Huang, H.J., 2018. An optimal charging station location model with the consideration of electric vehicle's driving range. Transp. Res. Part C Emerg. Technol. 86, 641–654. https://doi.org/10.1016/j.trc.2017.11.026.

Hu, H., Du, B., Liu, W., Perez, P., 2022. A joint optimisation model for charger locating and electric bus charging scheduling considering opportunity fast charging and uncertainties. Transp. Res. Part C Emerg. Technol. 141. https://doi.org/10.1016/j.trc.2022.103732.

Huang, D., Wang, Y., Jia, S., Liu, Z., Wang, S., 2023. A Lagrangian relaxation approach for the electric bus charging scheduling optimisation problem. Transportmetrica A Transport Science 19 (2). https://doi.org/10.1080/23249935.2021.2023690.

Hwang, I., Jang, Y.J., Ko, Y.D., Lee, M.S., 2018. System optimization for dynamic wireless charging electric vehicles operating in a multiple-route environment. IEEE Trans. Intell. Transp. Syst. 19 (6), 1709–1726. https://doi.org/10.1109/TITS.2017.2731787.

International Transport Forum (ITF). (2023). Life-Cycle Assessment of Passenger Transport: An Indian Case Study. International Transport Forum. OECD Publishing, Paris. https://www.itf-oecd.org/sites/default/files/docs/life-cycle-assessment-passenger-transport-india.pdf.

Jaramillo, P., Kahn Ribeiro, S., Newman, P., Dhar, S., Diemuodeke, O. E., Kajino, T., Lee, D. S., Nugroho, S. B., Ou, X., Hammer Strømman, A., & Whitehead, J. (2022). Transport. In P. R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), Climate change 2022: Mitigation of climate change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 1049–1160). Cambridge University Press. https://doi.org/10.1017/9781009157926.012.

Jiao, Y., Zhao, Y., Ma, C., 2023. Robust optimization of customized electric bus routes in village-town areas. Eng. Lett. 31 (2).

Kunith, A., Mendelevitch, R., Goehlich, D., 2017. Electrification of a city bus network—An optimization model for cost-effective placing of charging infrastructure and battery sizing of fast-charging electric bus systems. Int. J. Sustain. Transp. 11 (10), 707–720. https://doi.org/10.1080/15568318.2017.1310962.

Lin, Y., Zhang, K., Shen, Z.J.M., Ye, B., Miao, L., 2019. Multistage large-scale charging station planning for electric buses considering transportation network and power grid. Transp. Res. Part C Emerg. Technol. 107, 423–443. https://doi.org/10.1016/j.trc.2019.08.009.

Liu, Z., Song, Z., He, Y., 2018. Planning of fast-charging stations for a battery electric bus system under energy consumption uncertainty. Transp. Res. Rec. 2672 (8), 96–107. https://doi.org/10.1177/0361198118772953.

Perumal, S.S.G., Dollevoet, T., Huisman, D., Lusby, R.M., Larsen, J., Riis, M., 2021. Solution approaches for integrated vehicle and crew scheduling with electric buses. Comput. Oper. Res. 132, 105268. https://doi.org/10.1016/J.COR.2021.105268.

Pettet, G., Ghosal, M., Mahserejian, S., Davis, S., Sridhar, S., Dubey, A., Kintner-Meyer, M., 2021. A decision support framework for grid-aware electric bus charge scheduling. 2021 IEEE Power and Energy Society Innovative Smart Grid Technologies Conference, ISGT 2021. https://doi.org/10.1109/ISGT49243.2021.9372174.

Qin, N., Gusrialdi, A., Paul Brooker, R., T-Raissi, A., 2016. Numerical analysis of electric bus fast charging strategies for demand charge reduction. Transp. Res. Part A Policy Pract. 94, 386–396. https://doi.org/10.1016/j.tra.2016.09.014.

Rogge, M., van der Hurk, E., Larsen, A., Sauer, D.U., 2018. Electric bus fleet size and mix problem with optimization of charging infrastructure. Appl. Energy 211, 282–295. https://doi.org/10.1016/j.apenergy.2017.11.051.

Sistig, H.M., Sauer, D.U., 2023. Metaheuristic for the integrated electric vehicle and crew scheduling problem. Appl. Energy 339, 120915. https://doi.org/10.1016/J.APENERGY.2023.120915.

Teng, J., Chen, T., Fan, W. "David, 2020. Integrated approach to vehicle scheduling and bus timetabling for an electric bus line. J. Transp. Eng. Part A Syst. 146 (2). https://doi.org/10.1061/jtepbs.0000306.

The Energy and Resources Institute (TERI). 2024. Roadmap for India's Energy Transition in the Transport Sector. New Delhi, India: TERI.

Transit Intelligence. (2024). Market Assessment for Intercity Electric Buses in India. Transit Intelligence LLP: Bengaluru, India. https://greenmobility-library.org/public/uploads1/resource_attachments/Market%20Assessment%20for%20Intercity%20e-buses%20in%20India_Transit%20Intelligence_Final_June2024.pdf.

Tzamakos, D., Iliopoulou, C., Kepaptsoglou, K., 2023. Electric bus charging station location optimization considering queues. Int. J. Transp. Sci. Technol. 12 (1), 291–300. https://doi.org/10.1016/j.ijtst.2022.02.007.

UITP. (2020). KNOWLEDGE BRIEF.

Uslu, T., Kaya, O., 2021. Location and capacity decisions for electric bus charging stations considering waiting times. Transp. Res. Part D Transp. Environ. 90. https://doi.org/10.1016/j.trd.2020.102645.

Wang, Y., Huang, Y., Xu, J., Barclay, N., 2017. Optimal recharging scheduling for urban electric buses: A case study in Davis. Transp. Res. Part E Logist. Transp. Rev. 100, 115–132. https://doi.org/10.1016/j.tre.2017.01.001.

Wang, J., Wang, H., Chang, A., Song, C., 2022. Collaborative optimization of vehicle and crew scheduling for a mixed fleet with electric and conventional buses. Sustainability 14 (6). https://doi.org/10.3390/su14063627.

Wei, R., Liu, X., Ou, Y., Kiavash Fayyaz, S., 2018. Optimizing the spatio-temporal deployment of battery electric bus system. J. Transp. Geogr. 68, 160–168. https://doi.org/10.1016/j.jtrangeo.2018.03.013.

Wu, X., Feng, Q., Bai, C., Lai, C.S., Jia, Y., Lai, L.L., 2021. A novel fast-charging stations locational planning model for electric bus transit system. Energy 224. https://doi.org/10.1016/j.energy.2021.120106.

Xu, X., Yu, Y., Long, J., 2023. Integrated electric bus timetabling and scheduling problem. Transp. Res. Part C Emerg. Technol. 149, 104057. https://doi.org/10.1016/J.TRC.2023.104057.

Xylia, M., Leduc, S., Patrizio, P., Kraxner, F., Silveira, S., 2017. Locating charging infrastructure for electric buses in Stockholm. Transp. Res. Part C Emerg. Technol. 78, 183–200. https://doi.org/10.1016/j.trc.2017.03.005.

Yıldırım, Ş., Yıldız, B., 2021. Electric bus fleet composition and scheduling. Transp. Res. Part C Emerg. Technol. 129, 103197. https://doi.org/10.1016/J.TRC.2021.103197.

You, P., Yang, Z., Zhang, Y., Low, S.H., Sun, Y., 2016. Optimal charging schedule for a battery switching station serving electric buses. IEEE Trans. Power Syst. 31 (5), 3473–3483. https://doi.org/10.1109/TPWRS.2015.2487273.

Yu, J.M., & Lu, R.Z. (2013). The empirical study of battery exchange station location model, Advisor: Ying-Wei, Wang.

Zeng, Z., Qu, X., 2022. Optimization of electric bus scheduling for mixed passenger and freight flow in an urban-rural transit system. IEEE Trans. Intell. Transp. Syst. 24 (1), 1288–1298.

Zeng, B., Wu, W., Ma, C., 2023. Electric bus scheduling and charging infrastructure planning considering bus replacement strategies at charging stations. IEEE Access 11, 125328–125345. https://doi.org/10.1109/ACCESS.2023.3330369.

Zhou, Y., Wang, H., Wang, Y., Li, R., 2022. Robust optimization for integrated planning of electric-bus charger deployment and charging scheduling. Transp. Res. Part D Transp. Environ. 110. https://doi.org/10.1016/j.trd.2022.103410.