Review

Electric Bus Scheduling and Timetabling, Fast Charging Infrastructure Planning, and Their Impact on the Grid: A Review

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Abstract: Transit agencies are increasingly embracing electric buses (EB) as an energy-efficient and emission-free alternative to the conventional bus fleets. They are rapidly replacing conventional buses with electric ones. As a result, emerging challenges of electrifying public transportation bus networks in cities should be addressed. Introducing electric buses to the bus transit system would affect the public transit operation planning steps. The steps are network design, timetabling, bus scheduling, and crew scheduling. Regarding the functional and operational differences between conventional buses and electric buses, such stages should be changed and optimized to enhance the level of service for the users while reducing operating costs for service providers. Many mathematical optimization models have been developed for conventional buses. However, such models would not fit the electric buses due to EBs’ limited traveling range and long charging time. Therefore, new mathematical models should be developed to consider the unique features of electric buses. We present a comprehensive literature review to critically review and classify the work done on these topics. This paper compares the studies that have been done in this field and highlight the missing links and gaps in the considered papers, and the potential future studies that could be done. The considered papers cover the integration of timetabling and vehicle scheduling, recharging scheduling planning, and fast charging infrastructure location planning and its impacts on the grid. The main goal of this research is to highlight the research gaps and potential directions for future studies in this domain to encourage more realistic and applicable models and solution approaches for fully electric bus transit systems.

Keywords: electric bus scheduling; bus timetabling; charging station location; charging scheduling; impact on the grid

1. Introduction

Greenhouse gas emitting energy sources are responsible for global warming. Thus, replacing such energy sources with clean and renewable sources of energy has become crucial during the past few decades. According to Figure 1, transportation is one of the significant emission sectors, contributing 22% of the total CO₂ emissions. Road transport accounts for three-quarters of transport emissions and 15% of total CO₂ emissions [1]. For example, in the UK, the total emission from buses is around 4.3 million tons if we assume that the average emission rate is 822 g per km for each bus [2]. That is why public transport has become an attractive area for potential emission reduction [3]. Electrifying transportation is a way to address both urban air pollution and the energy crisis. The world is witnessing a rapid increase in electric vehicles and electric buses because of the increasing concerns about air quality, greenhouse gas emissions, and energy demand. The electrification of buses could significantly reduce environmental concerns, decrease the exploitation of natural resources, and provide better fuel economy and greater energy
efficiency [4]. According to [3], electrifying public buses will improve living conditions in metropolitan areas. Other advantages of using electric buses are their low noise levels and regenerative braking system for recovering energy [5]. On the other hand, EBs’ operational range is shorter than that of diesel buses, and their recharging process via depot charging is considerably more time-consuming than refueling. Furthermore, the costs of electric buses are significantly higher than conventional buses, due to the buses themselves and their batteries, charging infrastructure, and establishment costs.

The number of electric buses in cities worldwide has grown in recent years. A recent study by Bloomberg New Energy Finance Electric predicted that EBs will replace over 47% of the world’s total city bus fleet by 2025 [6]. Figure 2 illustrates the year-over-year growth of the battery-electric bus (BEB) fleet in European Union (EU) countries from 2021 to 2022 [7]. In 2017, 9% of all buses sold in Europe were EBs [8]. From 2022 to 2027, the market for electric buses in Europe is anticipated to grow by 18.6%. This shows the trend of switching from conventional buses to electric buses.

Cities are struggling to improve their public transport systems’ efficiency, especially bus transit systems. Operational processes are one of the most critical aspects of the bus transit system’s performance [9]. Bus timetabling (TT) and scheduling are among the
most vital processes in bus operations. Bus timetabling aims to collect departure and arrival times for all trips and routes in the network. It seeks to maximize passengers’ satisfaction \[10\] through minimizing the waiting time, transferring time, increasing seat availability, etc. The process of assigning vehicles to the trips of a specified timetable is known as vehicle scheduling (VS). It aims to use the minimum number of vehicles while minimizing operational costs. Bus scheduling has a notable impact on operational costs and passenger travel times. With the increase in electric buses, a new set of scheduling and timetabling problems has emerged. Electric buses’ limited driving range and long recharging times should be considered in the studies in this field. For example, charging during off-peak hours could reduce both the fleet size and impact on the grid. Thus, timetabling and bus scheduling should be coordinated and changed regarding the new constraints of electric buses to satisfy both bus operators’ and public users’ interests. Furthermore, to improve bus schedules, a reasonable charging strategy is required \[11\].

The limited traveling range of EBs has prompted new research in the literature on the problem of locating charging stations for electric buses. This task involves finding the best locations for fast-charging infrastructures on the bus transit network while determining the optimum number of such stations. Public transportation agencies introduced fast-charging technology with high voltage power to recharge e-buses in several minutes to address long charging times and limited driving range issues. On the other hand, fast-charging station location planning makes battery-electric bus scheduling more complex \[12\]. However, bus transit systems that use fast-charging technologies are gaining popularity. This approach needs extensive infrastructure for the installation of charging stations along bus routes. Moreover, compared to depot charging, charging stations at bus terminals are less expensive and more suited to bus electrification throughout the life cycle \[13\].

Most studies deal with public transit operation planning steps sequentially. This means that the output of an operational planning step would be the input of the subsequent step. The drawback of this approach is the inefficient public transit operation compared to the complete integration approach. The complete integration approach investigates the problem as a whole integrated problem that simultaneously considers each step of public transit planning. For instance, slight changes in the timetable of buses could result in a better vehicle schedule, and determining the location of fast charging infrastructures based on the bus schedules could reduce the operational costs of vehicle scheduling in a few years.

The Surveying Method

We wrote this review paper based on a methodological framework by choosing several keywords to look for papers that fit the scope of this article. The selected keywords were electric bus scheduling, electric bus timetabling, fast charging location, charging schedule fast charging infrastructure, vehicle to grid (V2G) and impact on the grid. After the articles’ titles and abstracts were initially reviewed, the relevant papers were thoroughly examined, their content was analyzed in detail, and each study’s methodology was explained. Google scholar was the scientific database used to track the articles that fall within the purview of this study. Table 1 illustrates the comparison of this survey with other review papers in this scope.

This literature review has been structured as follows: Different types of electric buses and their charging technologies will be discussed in Section 2. The theoretical background and related works of fast charging infrastructure location planning, scheduling, timetabling of electric buses, and the impact of electric buses’ charging stations on the grid are reviewed in Section 3. Section 4 describes the challenges and limitations of electric buses planning. Finally, Section 5 addresses future research, potential research directions, and gaps in earlier studies. Figure 3 represents a scheme of the group of problems that will be reviewed in this paper.
Figure 3. Problems that significantly impact the operation planning of EBs.

Table 1. Comparing different review papers with the current study.

<table>
<thead>
<tr>
<th>Review Paper</th>
<th>Comparing Charging Technologies</th>
<th>VS</th>
<th>TT-VS</th>
<th>Charging Infrastructure Location</th>
<th>Charging Scheduling</th>
<th>Impact on the Grid</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>[14]</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Reviewing environmental, economic, and energy efficiency of electric buses.</td>
</tr>
<tr>
<td>[15]</td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Categorizing planning, case studies, and simulation of electric buses.</td>
</tr>
<tr>
<td>[17]</td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>Future research on EBs will be strategies for energy and fleet management and sustainability.</td>
</tr>
<tr>
<td>[18]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>Integration of EB charging scheduling and vehicle scheduling for improving economic attractiveness.</td>
</tr>
<tr>
<td>This work</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Public transit operation planning integration and impact of charging stations on the grid.</td>
</tr>
</tbody>
</table>
2. Different Types of EBs and Charging Technologies

Electric buses are mainly divided into three groups, hybrid electric, fuel cell electric, and fully electric, as shown in Figure 4. The former is categorized as parallel, series, and series-parallel. In a parallel design, both the combustion engine and electric motors could propel the bus, unlike the series type, in which only the electric motor is used for the propulsion. The combustion engine supplies the energy of the electric motor. The combination of such two types is known as series-parallel, which benefits from the advantages of both types [14]. Hybrid electric buses can travel longer compared to fully electric ones, and they have very minor emissions. The issues related to this kind of bus are managing the sources of their energy and optimizing the sizes of engines and batteries. Fully electric buses only rely on electric power stored in their batteries to operate. They are not dependent on oil, so they have no emissions, and the travel range of such EBs is dependent on the capacity of the batteries. On the other hand, the high price of batteries and long charging time, along with the sparsity of charging stations, are the main issues of buses of this kind.

Different charging strategies for electric buses are fast/quick charging, depot/overnight charging, battery swapping, and continuous charging. Quick or fast charging requires a large amount of voltage to recharge buses in a short time (a few minutes). Depot or overnight charging refers to the charging poles which use less voltage to recharge buses but in a longer time. In battery swapping, electric buses’ batteries will be replaced with new charged ones. The last one, continuous charging, includes wireless charging and overhead lines. With this type, buses will be charged all the time during their trips. Table 2 summarizes the information about different charging technologies and bus features for each charging type (for more detailed information, readers are referred to [19]).

Table 2. Recommended features of buses and charging stations as a function of charging technologies.

<table>
<thead>
<tr>
<th>Type</th>
<th>Depot Charging</th>
<th>Fast Charging</th>
<th>Wireless/Continuous Charging</th>
<th>Battery Swapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery capacity (kWh)</td>
<td>Hybrid/fully electric</td>
<td>40–120 [20]</td>
<td>18.1 [21]—(123–201) [22]</td>
<td>324 [6], 320–590 [23]</td>
</tr>
<tr>
<td>Weight</td>
<td>More</td>
<td>Less</td>
<td>Less</td>
<td>Depending on the battery size</td>
</tr>
<tr>
<td>Transformer</td>
<td>No need to upgrade</td>
<td>Need to upgrade</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Grid stability</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td>Bus depot</td>
<td>Certain bus stops</td>
<td>Certain bus stops/bus depot</td>
<td>Specific spots</td>
</tr>
</tbody>
</table>

Table 3 represents the differences between conventional and fully electric buses in terms of environment, economic, and energy points of view (for more information, readers are referred to [28].) Note that the manufacturing and operational costs of electric buses and conventional ones vary, so the average costs are compared.
Table 3. Comparison of functional and operational differences between conventional buses and electric buses.

<table>
<thead>
<tr>
<th></th>
<th>Manufacturing Cost</th>
<th>Operational Cost</th>
<th>Infrastructure Cost</th>
<th>CO₂</th>
<th>Energy Efficiency</th>
<th>Range</th>
<th>Noise and Vibration</th>
</tr>
</thead>
</table>

1 BEB has the highest energy efficiency, with 6.76 MJ/km of fuel consumption, followed by FCEB (10.48 MJ/km) and series HEB (10.81 MJ/km).

The advantages and disadvantages of each charging technology follow (see Table 4):

2.1. Depot Charging

It has high efficiency and multiple charging levels. This charging technique could help reduce the grid’s power loss by using the vehicle-to-grid (V2G) configuration. Compared to fast-charging technology, this charging technology does not require upgrading in its lifetime. Additionally, it will provide higher grid stability and higher profits for bus depot operators. On the other hand, it has a complex infrastructure and is highly dependent on electricity grid restrictions. The weights and costs of buses that use this charging technique are higher in comparison to those employing other charging technologies. The recharging procedure is time consuming, as it takes 4 to 6 h to completely charge a battery. Moreover, if bus depot operators use a vehicle-to-grid configuration, the lifetime of batteries will decrease.

2.2. Fast Charging

This charging technique is the most efficient way to recharge electric buses in terms of time. The charging time is somewhere between 5 and 10 min. As the capacity of electric buses which use this charging technology is lower than that of buses that use depot or battery swapping technology, the weight and cost are lower. However, the travel range is limited. Additionally, the transformers of such charging techniques need to be upgraded, and this causes low grid stability. Low bus-depot-operator profits is another disadvantage of fast charging. For more information and explanations, readers are referred to [31,32].

Pantograph charging belongs to this category and is typically more costly and logistically difficult than depot charging. To establish charging stations along their routes, agencies might need to purchase land or right of way. Fast chargers, which are more expensive than slower chargers, are necessary for en-route charging. Due to demand charges and time-of-use rates, agencies have no control over when en-route charging takes place, resulting in expensive power expenditures. The placement of chargers in open outdoor areas has a variety of problems as well: pantograph chargers being deliberately damaged, a recycling truck demolishing charging infrastructure, complaints from neighbors who do not like having chargers next to their homes, and turning off below −20 °F are some
difficulties that transit agencies could encounter. It may be more difficult for agencies to repair or maintain fast chargers when these or other issues arise, since maintenance specialists must travel to get to them. Additionally, if one en-route charger is not working, it might occasionally affect the dependability of the transit service when relying on fast charging infrastructure [33]. The cost of pantograph charging stations for battery electric buses is much higher than stationary overnight depot charging. However, the battery cost for buses that use overnight charging is higher than that of fast-charging electric buses.

2.3. Battery Swapping

Quick battery replacement, benefits from V2G technology, and extended battery life due to slow charging are the main advantages of battery swapping technology. Nevertheless, a high initial cost and area utilization are the drawbacks of this technology. It requires a huge investment to rent a large area to store the batteries, a large number of expensive batteries, and equipment.

2.4. Wireless Charging

The recharging procedure is safe and convenient, and there is no need to stop for recharging. Furthermore, there is no need for a standard connector compared to conductive charging. On the other hand, it does not provide strong power, and it has a low range of power transmission. Moreover, it requires a huge amount of investment for en-route charging infrastructure on the roads.

Table 4. Advantages and disadvantages of different charging technologies.

<table>
<thead>
<tr>
<th>Charging Technology</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depot charging [34,35]</td>
<td>Multiple charging level, Providing V2G configuration, High efficiency, Less grid loss, No need to leases the property around the service area, The upfront capital cost is often cheaper</td>
<td>Batteries’ lifetime will decrease due to V2G operation, Long recharging time, Increase the number of deadhead trips to/from the depot, Larger battery packs, more weight and cost, Restrictions on placing bus routes due to EBs’ travel range limitation and deadhead trips to/from depot</td>
</tr>
<tr>
<td>Fast charging [31,32]</td>
<td>Less recharging duration, Cover longer bus routes compared to depot charging, Little time loss for recharging during the operation hours, Require smaller batteries</td>
<td>Voltage instability, High cost of fast charging infrastructure, Difficulty of placing fast chargers in tight and crowded city downtowns</td>
</tr>
<tr>
<td>Wireless charging [36,37]</td>
<td>Recharging process is safe and convenient without using any plugs, No need for socket and connector, Capability of recharge while the bus is moving</td>
<td>Huge investment cost for establishing on road infrastructure, Low range of power transmission, Weak power transfer</td>
</tr>
<tr>
<td>Battery swapping [38–40]</td>
<td>Fully charged batteries replaced in a short time, Prevent the battery capacity and lifetime fade by slow charging, Provide V2G configuration to balance the electricity demand and load</td>
<td>More expensive than conventional buses due to ownership or rent of a large battery swap station, Requires a large amount of budget for buying batteries, Requires a large area for swapping batteries and their equipment</td>
</tr>
</tbody>
</table>
3. Theoretical Background and Related Works

In this section, first, brief background regarding different types of charging station location planning approaches are described. Then, a detailed review of the literature on fast charging infrastructure locations and recharging planning is given. In the next part, a concise overview of bus scheduling and timetabling is presented, followed by a comprehensive investigation of studies focusing on the integration of bus scheduling and timetabling.

3.1. Charging Station Location Planning

There are several main approaches for locating charging infrastructures for electric vehicles, as follows:

3.1.1. Node-Based Approach

This approach would satisfy the charging demand by finding the best locations/nodes for chargers among the potential set of nodes. P-median and p-center are among the most common models to deal with node-based approaches. The p-median model minimizes the average distance between the charging demand nodes and the closest charging infrastructures [41]. In comparison, p-center aims to minimize the maximum distance between demand nodes and charging infrastructure location [42]. Baouche et al. [43] optimized the charging station locations concerning the p-dispersion constraint. The p-dispersion constraint would not allow the charging infrastructures to be placed at less than a predefined threshold. Other classic facility location approaches are maximal covering and set covering. The former seeks to cover the most charging demand of EVs [44], and the latter tries to minimize the total installed charging infrastructures while satisfying all the charging demands [45].

3.1.2. Flow-Based Approach

The flow-based approach is more suitable than the node-based approach for vehicles, since the cars move along the roads instead of remaining idle at specific nodes. Kuby and Lim [46] developed a flow-refueling location model based on the flow-capturing approach to find the best locations for refueling stations. Maximizing the total volume of flow was the objective of this study.

3.1.3. Path-Based Approach

Unlike the past two approaches, which focused on flows or nodes, the path-based focuses on vehicles paths. Path refueling location model and sub-path location model are the two branches of this approach. The objective is to find the best places for the charging infrastructure on the path, to ensure that vehicles can complete their trips on that path [47,48].

3.1.4. Equilibrium-Based Approach

This approach analyzes the impact of charging stations’ locations on the travel behavior of electric vehicle drivers [49,50]. An equilibrium modeling framework was presented by He et al. [51] to maximize the social benefit regarding the plug-in hybrid electric vehicles (PHEV) recharging routing. The objective of the study was to find the best places for charging stations for PHEVs. They considered the availability of charging stations, route choice of electric vehicles, and electricity price to formulate a mathematical allocation model.

According to [52], the path-based approach is the most common approach for solving charging station location problems for electric buses. Such problems are classified into two categories: charging lanes and charging stops. The former has attracted significant attention recently and is the most advanced charging technology. In [53], wireless charging location planning for lanes and optimizing battery capacity were studied, and particle swarm optimization was used to find the best location and optimum battery capacity. Liu and Song [54] studied the same problem while considering the uncertain nature of electric buses’
energy consumption. They dealt with the uncertainty of buses’ energy consumption and travel time by adopting a robust optimization approach followed by the affinely adjustable robust counterpart (AARC). In a more recent study, Helber et al. [55] investigated the wireless charging location planning for an airport’s electric shuttle buses. For the latter, electric buses are supposed to be charged only at several specific spots on the road network. Kunith et al. [56] presented a capacitated set-covering problem to solve a joint fast-charging infrastructure location and battery capacity problem. The authors developed a mixed-integer linear programming (MILP) formulation to find the optimum number of chargers and their optimal locations. For inductive and conductive charging infrastructure planning, Xylia et al. [57] studied a case study in an urban context in Stockholm. The objective was to minimize the total energy consumption and operational costs of the system.

In the overnight or depot charging strategy, the locations of depots is a critical factor. Charging’s impacts on the grid [58], the establishing costs of charging stations, and operational costs such as deadhead trips would be affected by charging station locations [59]. Another important issue addressed by [60,61] is the trade-off between the accessibility of overnight charging stations and the total establishment cost of such stations. Moreover, the possibility of upgrading existing depots with charging infrastructure should be considered [52], as should the locations where the continuous charging infrastructure is to be and how the electrified distance of the road affects the network planning of bus lines too. There is no paper considering the effects of wireless charging on the network route design of bus lines. By introducing fast chargers for electric buses, a group of new location planning problems has emerged in the scope of the network design problem. Fast charging infrastructures are new inputs for the network route design, and the best locations for bus stops and such infrastructures should be considered simultaneously [62].

Fast Charging Infrastructure Location Planning (FCILP)

Electric buses have not yet gained widespread adoption compared to other electric vehicles due to their high ownership and operating costs, their long charging times, and the uneven spatial distribution of charging infrastructure. Furthermore, dynamic environmental factors, such as unanticipated traffic congestion, varying travel demand, and even different weather conditions, can considerably impact electric buses’ charging efficiency [63]. Another critical factor is the lack of adequate charging infrastructure for large-scale EB fleets. As a result, studying the location planning of charging infrastructure for electric buses is essential. Pantograph chargers can decrease the number of deadhead trips to and from the depots, decrease the battery capacity, and minimize energy usage compared to standard overnight/depot charging. Although fast-charging technologies can shorten the time it takes for buses to charge, they significantly increase operational costs. As a result, the costs of installing and planning of fast-charging stations should be factored into the planning process. The simple formulation of charging station location planning is presented in the Appendix A.3. Kunith et al. [64] performed one of the first studies of fast charging infrastructure planning in 2014. They aimed to find the optimum number of fast chargers and their best locations in the network, considering the operational constraints. The distribution and bus operating networks have been considered for this problem in [65]. The model’s goals were to reduce the total installation costs of fast chargers, their operating and maintenance expenses, travel cost to the chargers, and the cost of their power loss. To find the number of required fast charging infrastructure, the affinity propagation method was used, and the best locations of chargers and their optimum capacities were obtained by binary particle swarm optimization (BPSO). Another optimization method to deal with the fast charging infrastructure location planning is enhanced heuristic descent gradient (EHDG). Othman et al. [66] used this algorithm to find the optimum locations for placing fast chargers. Csonka [67] solved the problem for both static and dynamic charging to find the best locations for charging infrastructures. Static charging and dynamic charging refer to conductive charging stations and overhead wire charging lanes, respectively. The amount of charging in each charging event was a decision variable in this study.
Bus systems that use fast-charging technologies are gaining popularity. This trend necessitates extensive studies on optimizing the location planning of establishing charging station infrastructures along bus routes. Kunith et al. [56] proposed a mixed-integer linear programming model to simultaneously optimize electric buses’ fast-charging infrastructure planning and battery capacity for each line. Through a set covering problem, the best locations and the optimum number of chargers were determined. He et al. [68] addressed the same problem by considering installing an energy storage system to store the energy in off-peak hours and supply it to fast-charging infrastructure in on-peak hours. A reduction of 9.2% in the total system costs was the result of this study compared to Kunith et al.’s outcome [56]. Olmos et al. [69] investigated the problem of locating opportunity charging infrastructure for hybrid and fully electric buses to find the best locations for such facilities. The two other objective functions in their paper were the power rates of opportunity charging infrastructures and the sizes of energy storage systems. Battery aging and partial charging for the problem of charging station location were considered in [70]. The objective was to reduce total costs, which included the price of establishing charging stations and the costs of purchasing the vehicles to be used. Liu et al. [71] dealt with the problem while considering uncertain energy consumption for battery-electric buses. They developed a mixed-integer linear programming model based on a robust optimization approach to find the minimum total implementation cost. The combination of charging station location planning and the power grid was studied in the paper of Lin et al. [52] in 2019. Other extensions of this problem are determining the best capacity for e-buses [56], designing transit route networks [62], and determining charging schedule for each fast-charging infrastructure [12].

In a recent study by Hu et al. [72], the combination of opportunity charging location and the charging scheduling problem of EBs was studied. They considered time-of-use electricity pricing and added the waiting time of passengers due to the charging process during the trips as a penalty cost. They aimed to minimize the cost of purchasing both opportunity chargers and electric buses’ batteries, reduce the total charging costs, and minimize the passengers’ extra waiting time. To address the uncertainties related to trip time and passenger travel demand, a robust optimization technique was suggested.

The combination of depot charging planning and electric bus scheduling (EBS) was considered in the paper of Olsen and Kliewer [73]. The objective was to minimize the total cost, including those of installing depot chargers, vehicle costs, and operating costs. A meta-heuristic solution approach based on variable neighborhood search (VNS) was developed to solve this problem. They showed that simultaneously optimizing these two problems would yield better results than sequential planning. The multi-depot and multi-vehicle-type version of this problem for refueling charging stations was studied by Li et al. [74] in 2019. They aimed to minimize the numbers of required buses and refueling stations, maintenance costs, energy consumption, and external emission costs. They developed an integer linear program to solve the small-scale problems and proposed a time-space bus flow network to deal with large-scale problems. Alwesabi et al. [21] presented a mixed-integer linear programming formulation to simultaneously find the optimum fleet size, battery capacity, and dynamic wireless charging locations. The combination of electric bus scheduling and fast charging infrastructure location planning has not been widely studied in the literature. The most similar research was the work of Stumpe et al. [75]. The authors studied the simultaneous optimization of electric bus scheduling and opportunity charging location planning. They proposed a new mixed-integer linear formulation and solved it using VNS.

Some public transit operators cooperate with companies that provide operational and strategic planning services. Li et al. [76] examined the fast-charging-infrastructure location planning in Chengdu under the build-operate-transfer (BOT) model. The transit agency tries to minimize the present value of deadhead trips and charging services. They addressed the location problem in a multistage scenario due to the gradual transport electrification. Fast-wireless-charging-infrastructure location planning considering the impact of delays caused by buses queuing up to charge at charger locations was studied by Tzamakos
et al. [77]. They developed a MILP model to minimize the total expenses of building wireless charging. The details of each study are presented in Table 5.

Since the electric power demand of fast charging infrastructures is high, and charging during peak hours would put much pressure on the grid, charging scheduling of EBs using such charging technology is challenging. Without paying attention to charging scheduling, the energy cost of this charging type would heighten, and the economic viability of switching to electric bus transit systems would be lower. He et al. [12] addressed this problem by proposing a network modeling framework. They minimized the total charging costs, including energy and electricity demand charges. (For more information, see [12]). Another critical issue of implementing fast-charging infrastructures for electric buses is the congestion of EBs at the charging stations due to the lack of available stations. Abdelwahed et al. [78] addressed this issue by presenting two mixed-integer linear programming models. They also considered the impact of the recharging schedule on the grid by considering off-peak and on-peak charging periods. One way to deal with the congestion of electric buses at fast charger stations is the bus-holding strategy. Gkiotsalitis [79] determined the best departure times of buses based on bus-holding strategy while considering the scheduled charging times. Minimizing the charging time of EBs during the service time was studied by Patil et al. [80].

Wang et al. [81] proposed an optimization model to find the best recharging schedule for electric buses while considering planning decisions such as finding the best number of chargers, their locations, and station capacity. The combination of optimal charging scheduling of electric buses and drivers’ mealtime time window has been discussed in [82]. Battery degradation and bus-to-grid (B2G) technology were studied by [83] for battery electric bus charging optimization. The objective was to minimize the charging cost of a real case study in Portugal. They provided a mixed-integer linear programming model for this problem and solved it with IBM ILOG CPLEX. There are other approaches, such as Lagrangian relaxation for depot charging [84], the progressive hedging algorithm (PHA) for both fast charging and battery swapping [85], and the genetic algorithm (GA) [86] that could be adopted to deal with the charging scheduling of electric buses.
### Table 5. Comparison of different studies on EBs’ charging infrastructure location planning.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Objectives and Decision Variables</th>
<th>Charging Type</th>
<th>Model</th>
<th>Algorithm</th>
<th>Case study</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kunith et al. (2014) [64]</td>
<td>Optimum number of fast charging stations; min construction cost</td>
<td>Fast charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>-</td>
<td>Considering battery charging behavior and operational constraints</td>
</tr>
<tr>
<td>Kunith et al. (2017) [56]</td>
<td>Best locations and the optimum number of chargers and battery capacity</td>
<td>Fast charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Berlin, Germany</td>
<td>Capacitated set covering problem</td>
</tr>
<tr>
<td>Rogge et al. (2018) [61]</td>
<td>Min the total cost of ownership</td>
<td>Depot charging</td>
<td>MILP</td>
<td>Grouping genetic algorithm</td>
<td>Germany &amp; Denmark</td>
<td>Min vehicle investment, charger investment, operational costs, and energy expenses</td>
</tr>
<tr>
<td>Rohrbeck et al. (2018) [70]</td>
<td>Min total costs: the price of establishing charging stations and purchasing cost of vehicles</td>
<td>Opportunity charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Mannheim, Germany</td>
<td>Considering battery aging, traffic congestion, and partial charging</td>
</tr>
<tr>
<td>Liu et al. (2018) [71]</td>
<td>Min the cost of installing fast-chargers and batteries</td>
<td>Fast charging</td>
<td>MILP</td>
<td>AARC</td>
<td>Utah, United States</td>
<td>Considering uncertain energy consumption for battery-EB</td>
</tr>
<tr>
<td>He et al. (2019) [68]</td>
<td>Minimizing the total cost of installing fast chargers, ESS, and EB batteries</td>
<td>Fast charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Utah, United States</td>
<td>Showing how the ESSs may save system costs by lowering demand charges</td>
</tr>
<tr>
<td>Olmos et al. (2019) [69]</td>
<td>Best location of chargers, power rate of charging infrastructures, and size of ESS</td>
<td>Opportunity charging</td>
<td>-</td>
<td>Iterative sequence</td>
<td>Donostia, Spain</td>
<td>Minimizing the total cost of ownership</td>
</tr>
<tr>
<td>Lin et al. (2019) [52]</td>
<td>Min the total operating, establishing, and grid power loss costs</td>
<td>Fast charging</td>
<td>MISOCP</td>
<td>Spatial-temporal approach</td>
<td>Shenzhen, China</td>
<td>Multistage planning model</td>
</tr>
<tr>
<td>Liu &amp; Ceder (2020) [87]</td>
<td>Min the required number of EBs and fast charging infrastructure</td>
<td>Fast charging</td>
<td>DF and IP</td>
<td>Adjusted max-flow</td>
<td>Singapore</td>
<td>lexicographic method-based two-stage construction-and-optimization solution was adopted to solve the bi-objective problem</td>
</tr>
<tr>
<td>Othman et al. (2020) [66]</td>
<td>Min the operational costs and energy consumption</td>
<td>Fast charging</td>
<td>EHDG</td>
<td>Voronoi diagram</td>
<td>Toronto, Canada</td>
<td>The proposed EHDG algorithm is based on genetic algorithm and gradient descent technique</td>
</tr>
<tr>
<td>Liu et al. (2020) [59]</td>
<td>Min operating costs; all backup buses, drivers, maintenance, energy consumption cost, and construction costs of charging depots</td>
<td>Depot charging</td>
<td>MILP</td>
<td>Artificial fish swarm algorithm</td>
<td>China</td>
<td>Optimizing the layout of bus routes, the service frequency, and the location of charging depots</td>
</tr>
<tr>
<td>Zhang et al. (2021) [62]</td>
<td>Total costs of user and operator unsatisfied demand, passengers’ travel time, and operator cost</td>
<td>Fast charging</td>
<td>MINLP &amp; MILP</td>
<td>Modified genetic algorithm</td>
<td>Swiss</td>
<td>Bi-level programming framework</td>
</tr>
<tr>
<td>Uslu &amp; Kaya (2021) [60]</td>
<td>Min the total cost; optimal locations and capacities of EB charging stations</td>
<td>Depot charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Turkey</td>
<td>Driving range has the highest effect for selecting locations and capacities of charging stations at minimum cost</td>
</tr>
<tr>
<td>Wu et al. (2021) [65]</td>
<td>Min maintenance, fast charging station construction, travel to charging stations costs and power loss of fast chargers</td>
<td>Fast charging</td>
<td>BPSO</td>
<td>Mathematical program</td>
<td>Yangjiang, China</td>
<td>The bus terminuses clustered by the Affinity Propagation approach in order to estimate the approximate number of charging stations</td>
</tr>
<tr>
<td>Olsen et al. (2021) [73]</td>
<td>Min the total cost of installing depot chargers, vehicle, and operating costs</td>
<td>Opportunity charging</td>
<td>VNS</td>
<td>-</td>
<td>-</td>
<td>They proved that complete integration of BEB scheduling and charging station location planning is better than sequential planning</td>
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</tbody>
</table>
Table 5. Cont.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Objectives and Decision Variables</th>
<th>Charging Type</th>
<th>Model</th>
<th>Algorithm</th>
<th>Case Study</th>
<th>Remarks</th>
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<tr>
<td>Alwesabi et al. (2021) [21]</td>
<td>Min the battery cost, system inverters, and total cable cost</td>
<td>Wireless charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Binghamton University</td>
<td>Finding the optimum fleet size, battery capacity, and dynamic wireless charging locations, simultaneously</td>
</tr>
<tr>
<td>Stumpe et al. (2021) [75]</td>
<td>Min the number of required vehicles, personnel and energy consumption costs</td>
<td>Opportunity charging</td>
<td>VNS</td>
<td>MILP</td>
<td>-</td>
<td>They performed sensitivity analysis for different input parameter uncertainties</td>
</tr>
<tr>
<td>Tzamakos et al. (2022) [77]</td>
<td>Min the number of wireless chargers</td>
<td>Wireless charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>-</td>
<td>M/M/1 queuing model was used for bus recharging queuing</td>
</tr>
<tr>
<td>Li et al. (2022) [76]</td>
<td>Min the deadhead trips and charging services</td>
<td>Fast charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Chengdu, China</td>
<td>The fast charging infrastructure location planning was investigated under the BOT model</td>
</tr>
<tr>
<td>Hu et al. (2022) [72]</td>
<td>Min the total cost of system; buying new chargers, EBs' batteries, charging cost and passengers' extra waiting time</td>
<td>Opportunity charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Sydney, Australia</td>
<td>Robust optimization technique was used to deal with the uncertain passengers' travel demand and trip time</td>
</tr>
<tr>
<td>Wang et al. (2022) [88]</td>
<td>Min the fleet size, EBs; batteries, and installing pantograph chargers costs</td>
<td>Opportunity charging</td>
<td>MILP</td>
<td>standard solver</td>
<td>Oslo, Norway</td>
<td>Time-dependent dwelling time, ridership, and travel time of BEBs were considered</td>
</tr>
</tbody>
</table>

1 In depot. 2 At bus stop. 3 In terminal. 4 In a specific station.
3.2. Bus Timetabling

A “good” timetable has different meanings from passengers’ points of view. One may recognize a good timetable by its regularity, whereas another will prefer a timetable with the exact headway or frequency that he wants; or a good-quality timetable may be represented by the minimum difference between the actual and desired frequency. Thus, determining a timetable would be challenging due to several objectives that should be satisfied. Minimizing the waiting times of passengers and maximizing the bus-line-departures synchronization are the main objectives of timetabling. Improving safety, quality of service, and comfort are the other objectives of the bus timetabling problem.

Researchers addressed the timetabling problem from various angles. Multi-objective models, which simultaneously reduce the passengers’ waiting times and increase bus utilization [89–91], maximizing bus frequencies to satisfy the passengers’ travel demands [92], and maximizing uniform loading on buses through even-load headways [93]. According to [94], depot charging does not affect electric bus timetables. Thus, the timetabling approaches and their methods for conventional buses could be implemented on EBs without any modifications. However, fast-charging affects the development of bus timetabling. The time taken for charging, which is about 5 to 10 min, should be considered when generating the timetable. Although fast-charging technology affects the timetabling problem (the recharging time should be added as an input to the problem), there is no study in the literature modeling the problem of electric bus timetabling specifically. Note that overnight and continuous wireless charging have no impact on generating timetables. According to [94], the methods to deal with the timetabling problem for conventional buses could also be implemented on EBs.

Ceder et al. [95] presented a mixed-integer model to create timetables with the maximum synchronization of bus arrivals at transfer stops. Since the suggested mixed-integer programming model belongs to an NP-hard set of problems, a heuristic approach was presented to solve the large-scale problems. Liu et al. [96] solved this problem using the Nesting Tabu Search algorithm. Ibarra-Rojas and Rios-Solis [97] solved this problem while avoiding bus bunching of bus lines. Minimizing the passengers’ waiting times has been addressed in [98] through optimizing the synchronization of bus arrivals at the connection nodes in the network. The authors solved the problem by formulating a MILP model. Parbo et al. [99] investigated the maximal synchronization problem to minimize the passengers’ waiting times by focusing on the social benefits of the created timetable.

Ceder et al. [89] developed a multi-objective model to reduce the expected waiting times of randomly arriving passengers while increasing bus utilization from the operator’s perspective. Zhang et al. [91], in 2020, proposed a decomposition heuristic algorithm to solve the multiple-vehicle-types scheduling problem and introduced a bi-objective optimization model for a feeder bus line to reduce operating costs and passenger waiting times with consideration of three different types of buses.

Shang et al. [92] proposed a timetabling problem for maximizing bus frequency and headway based on customer satisfaction. The timetabling is optimized by striking a balance between customer satisfaction and bus transit performance, taking the load factor into account. Ceder and Philibert [93] developed an approach for creating even-load transit timetables to achieve a uniform maximum load on vehicles and seamless transfers. Due to the low load discrepancy, such even-load timetables would improve vehicle utilization and minimize empty seat-minutes. However, they would prolong the waiting periods for passengers arriving at random stops. Gkiotsalitis and Alesiani [100] presented a robust timetable using a bus movement mathematical model which incorporates travel times and passenger demand uncertainty to reduce the potential loss in worst-case scenarios by minimizing the deviation between actual departure times of buses and the desired ones.
3.3. Bus Scheduling

The process of assigning buses to the trips of a specified timetable is known as vehicle scheduling (VS). The set of trips from the timetable is fed into the vehicle schedule, aiming to cover them as efficiently as possible while meeting all operational constraints, typically by reducing the required bus numbers and deadhead trips. Both exact and heuristic/metaheuristic solution approaches are adopted to solve this problem [101,102]. Vehicle scheduling with one depot and multi depots are the two main categories of bus scheduling. The single-depot vehicle scheduling problem can be solved in polynomial time, whereas multi-depot vehicle scheduling belongs to the class of NP-hard problems. The time-space network is another framework for modeling vehicle scheduling problems. In this framework, nodes represent the departures and arrivals of buses at a certain time and location, and arcs represent the travel between nodes by a vehicle. The simple formulation of electric bus scheduling is presented in the Appendix A.2.

Another approach to deal with bus scheduling problems is deficit function (DF) modeling. References [103–105] used this method to find the optimum required number of vehicles and assign them to the predetermined timetable based on DF theory. The applications of this theory to network design and crew scheduling of public transit operation planning were investigated by [105]. The deficit function’s visual aspect is its key benefit. Readers are directed to [106] for a thorough explanation of the fundamental theory and significant advancements in DF modeling and applications.

Driving range limitation and long time recharging process for electric buses are the two factors which alter the conventional models and solution approaches of vehicle scheduling problems. EBs have range limitations and should be recharged at bus depots, terminals, or bus stops, depending on the charging technology, a few times a day. This would necessitate studying electric bus scheduling from the economic and operational points of view. Li [107] showed the changes to the bus scheduling process after introducing electric buses.

3.3.1. EB Scheduling with Heuristic Solution Approaches

Wang and Shen’s paper [108] is one of the first studies in electric bus scheduling with a limited travel range and minimum recharging time. The objectives were to minimize the number of buses and decrease the total time of deadhead trips. The authors solved the problem by ant colony optimization (ACO) algorithm. Zhu and Chen [109] addressed this problem in a single-depot VSP form. They considered a battery swapping strategy for charging electric buses. Minimizing the cost of ownership of buses and their extra batteries and minimizing the charging costs were the two objectives of this study. The solution approach was based on non-dominated sorting genetic algorithm II (NSGA-II) to present optimal Pareto fronts for a case study in China. Paul and Yamada [110] addressed the charging and operation scheduling of electric buses and the operating of conventional buses for four bus lines. They aimed to maximize the EBs’ total travel distance and decrease the amount of CO2 emissions and fuel cost. The authors solved the proposed problem by a k-greedy algorithm and validated it through a simulation process using real data from a case study in Japan. Simulation models could be adopted to solve electric bus scheduling too. Sung et al. [111] sought to minimize the cost of charging stations, batteries, and buses, and electricity consumption using a simulation model and a heuristic algorithm was developed to solve the problem. This study’s main outputs are buses and charging stations’ optimum number and type. Other metaheuristic solution methods and their combinations were used to determine the optimum departure times of buses. Ke et al. [112] combined GA, PSO, and SA to minimize the electricity costs and total emissions of greenhouse gases. Joint optimization of EB scheduling and crew scheduling for a heterogeneous bus fleet (traditional and electric buses) were studied in [113]. A bi-level programming model was provided to minimize the economic and operational costs of CO2 in the upper level and minimize the drivers’ wage while increasing the bus-driver specificity (the same driver operates the same bus) in the lower level. To solve this problem, a PSO algorithm was adopted based on an epsilon constraint method.
The adaptive genetic algorithm (AGA) is another approach to solving the vehicle scheduling problem. Li et al. [114] used this method to tackle the integration of electric bus scheduling and stationary charger deployment for a real case study in Anting Town, Shanghai. They considered partial charging and time-varying electricity prices and tried to minimize the total construction and maintenance cost of electric bus scheduling and charging infrastructure. Uncertainties in the number of arriving passengers, their waiting times and the energy consumption of electric buses were considered in [115] to find the optimum departure intervals of EBs. The problem was solved based on an uncertain bi-level programming model (UBPM). The upper level seeks to minimize the passengers’ travel costs, and the lower level tries to minimize the energy consumption of electric buses. GA was adopted to solve a real case study in Nanchang, China. Additionally, reducing power consumption and in-service costs were included in the objective function. A multi-vehicle version of electric bus scheduling was studied by Yao et al. [116] in 2020. They aimed to reduce the required investment for buying electric buses and charging infrastructures while minimizing the operational costs of deadhead trips. Since the problem was an NP-hard one, a heuristic approach was adopted to solve it in a reasonable time. A bi-objective integer programming approach was developed by Liu and Ceder [87] to minimize both the total number of EBs and required fast charging infrastructures in a multiple bus line transit system with a partial charging policy. To solve this problem, the authors suggested two methods: a lexicographic and a modified max-flow approach. They implemented their model in a real case study in Singapore. The collaborative optimization of electric bus scheduling and charging scheduling was studied in [117]. This study provided a multi-objective bi-level programming model to minimize carbon emissions and operating costs, including deadhead trip costs, passenger trip costs, and power consumption costs. An iterative neighborhood search and a greedy dynamic search strategy were adopted to solve the electric bus scheduling and charging scheduling, respectively. Zhu et al. [118] solved the IoT electric bus scheduling based on a new metaheuristic solution named the phasmatodea population evolution (PPE) algorithm, and they obtained a smaller loss value in comparison with the PSO algorithm.

3.3.2. EB Scheduling with Exact Solution Approaches

Alwesabi et al. [119] studied the EB scheduling problem by minimizing the total cost, by finding the optimum number of electric buses and taking into account the number of charging stations and battery size limitations. Li [107] investigated scheduling of electric buses which use fast chargers or battery swapping technology. He also studied this problem with a limited travel range form for buses with different sources of energy. Mixed-integer programming models have been proposed for these problems. The author believes that the proposed model could be used for both charging types, since the battery swapping time is approximately equal to the fast-charging time. To deal with this scheduling problem, column generation algorithm was used. Rinaldi et al. [120] studied the scheduling problem of electric buses with a service factor and charging-factor constraints to determine the sequence of electric and hybrid buses departing from a multi-line bus terminal. They presented a mixed-integer linear program to minimize the total operation costs. In 2020, Tang et al. [121] addressed the electric bus scheduling problem by presenting static and dynamic scheduling models to reduce the total operating costs and expected costs through introducing a buffer-distance strategy and rescheduling buses regarding the updated traffic condition. They solved the problem with a branch-and-price algorithm.

According to [105], multi-depot vehicle scheduling problems are split into two parts: determining the trip chains and assigning buses to each trip. The introduction of EBs has a larger impact on the former, since the trip chains should be modified regarding the limited travel range of EBs. Jiang and Zhang [122] addressed this problem with a partial charging policy and vehicle-depot constraint (the starting point and end point of EBs trips should be at the same depot). They developed a MILP and solved it using a branch-and-price algorithm. Gkiotsalitis et al. [123] considered time windows for the multi-depot electric bus
scheduling problem. They aimed to minimize buses’ costs and waiting times by proposing a mixed-integer nonlinear program. They linearized the model and solved it using a branch-and-cut algorithm based on valid inequalities. A multi-vehicle-type electric vehicle scheduling problem with a limited battery capacity constraint was discussed by Reuer et al. [124]. They solved the problem using a time-space network. Multi-depot electric bus scheduling with a partial charging policy for a heterogeneous fleet was investigated by Zhang et al. [125], in 2022. The objective function was to minimize the purchase cost of EBs and operational costs. They proposed a MILP and solved it using an adaptive large neighborhood search algorithm. Wu et al. [126] solved the problem by taking the time-of-use and peak load of the power grid into account. They aimed to reduce the peak charging demand and overall operating costs, and to do that, they developed a MILP based on a time-expanded network and solved it using a branch-and-price algorithm.

Van Kooten Niekerk et al. [127] proposed two models for battery electric bus scheduling with a limited-travel-range constraint—one with different assumptions, such as assuming linear chargeability of buses, neglecting to consider the time-of-use (TOU) electricity price, and neglecting the impact of depth-of-discharge (DOD). The second model was more realistic by relaxing the mentioned assumptions. By introducing integer linear programming, the suggested model for this problem could be solved in a reasonable time for small and medium-scale problems. The authors presented two other techniques based on the column generation approach to find near-optimum solutions for large-scale problems. As stated in [81], by adopting the best recharging strategy, the travel range limitation of EBs could be addressed and eliminated. Thus, the aim of the research was to find the best strategy for recharging electric buses. Finally, the authors implemented their model for a real case study in California. Joint optimization of pantograph charger location planning, BEB scheduling, and battery capacity were addressed in [88]. The aim was to reduce the total annual cost associated with the fleet, and they developed a MILP to deal with the problem.

3.4. Integration of Bus Scheduling and Timetabling

This portion of the literature discusses the integration of timetabling and vehicle scheduling problems. Häll et al. [94] studied the EBs timetabling and vehicle scheduling changes, seeking to optimize various charging methods, including continuous, overnight, and quick charging. The authors investigated the effects of introducing EBs on public transportation’s operational planning (transit network, timetabling, and scheduling). Integration of electric bus timetabling and vehicle scheduling is required to meet passengers’ demands, enhance social benefits, and reduce operator costs [90]. Hence, finding the optimal timetable and vehicle schedule for electric buses is a key factor in reaching a more sustainable transit system. Most previous studies considered bus scheduling and bus timetabling individually and separately. Ceder et al. [128] and Chakroborty et al. [129] were the first researchers who studied the integration of TT and VS. Ceder et al. addressed an approach for combining timetables and vehicle scheduling from both the customer and the operator’s perspective to reduce the fleet size. Their approach was based on a four-step sequential method with a feedback loop. Chakroborty et al. addressed the problem without the interlining option and minimized the fleet size while reducing passengers’ transfer and waiting times, based on a genetic algorithm approach. Most of the studies in the literature mainly discuss the minimization of passengers’ waiting and travel time for timetabling and minimization of bus operator costs (purchase costs of new buses, deadhead trip costs, scheduling, and recharging costs).

The combination of bus timetabling and scheduling is a bi-objective problem. On the one hand, it should optimize the passengers’ satisfaction by minimizing waiting time, travel time, seat availability, and so on; on the other hand, it should consider operational costs from the bus companies’ point of view. These two objectives are in conflict, and to solve and handle such issues, several strategies could be adopted: shifting, weighting, Pareto front, bi-level programming, and reordering.
In shifting, VS could be solved with minor changes in the timetable, i.e., small shifts in arrival and departure times to reduce the operational costs of scheduling. In this approach, a selected objective function would be optimized regardless of another objective function on the condition that the second objective will not exceed/be less than a given threshold value. Kliewer et al. [101] were the first scholars who introduced shifting strategy for vehicle scheduling problem, which is called the vehicle scheduling problem with time windows (VSP-TW). They used a time-space network to find out the feasible combinations of trips and solved the problem using heuristic and column generation methods. Fleurent et al. [130] and Van den Heuvel et al. [131] extended the model presented by Kliewer et al. [101], proposed a hierarchical approach to solve the vehicle scheduling problem, and used mathematical programming models to find the best number of vehicles and optimize the type of vehicles based on a simulated annealing (SA) approach. A combination of shifting and weighting strategies based on a metaheuristic approach was developed by Fonseca et al. [132]. They aimed to minimize the total operational costs while minimizing the passengers’ transfer times.

The weighting strategy is one of the most straightforward strategies to dealing with such a problem, but the issue is determining the weights’ best values to describe the preferences of passengers and public transportation service providers. Petersen et al. [133] introduced a new problem to simultaneously address passengers’ waiting time and total resource costs for an integrated TT and VS problem. They solved the model based on the large neighborhood search (LNS) metaheuristic solution approach and used the weighted sum method to deal with the bi-objective nature of the problem. Carosi et al. [134] looked at vehicle scheduling and timetabling and used the weighted objective function to prove that the integrated timetabling and vehicle scheduling problem is a bi-objective problem. Furthermore, they proposed a multicommodity-flow-style mixed-integer linear programming model to balance service providers’ costs and customer satisfaction optimally.

In another paper, Guihaire and Hao [135] proposed an iterative local search method to solve the integrated timetabling and vehicle scheduling (ITTVS) problem. The objectives of the problem were minimizing the operational costs of vehicles and maximizing the service quality. The latter objective was measured by evenness of headways, and the former was calculated with respect to the lengths of the deadhead trips and fleet size. Schmid and Ehmk [136] addressed the ITTVS problem with a degree of flexibility to change the timetable and balanced departure times and solved it based on the large neighborhood search (LNS) approach. The two objectives were improving the quality of timetable and reducing the operating costs, which were optimized using the weighted sum approach.

Another strategy is using the Pareto front. This strategy aims to find the Pareto optimal front, which any other solutions would not dominate. Ibarra-Rojas et al. [137] solved timetabling and vehicle scheduling individually by introducing two integer linear programming formulations. Then, they combined the two problems into a bi-objective integrated problem. The method used to deal with this bi-objective model was based on the epsilon constraint method. The authors believe that their proposed model and solution approach could solve the problem for up to 50 bus lines. A combination of timetabling and VS was also suggested by Weiszer et al. [138] in 2010. The suggested model included two objective functions: minimizing passengers’ waiting times at each bus stop and minimizing the required number of buses to cover all the trips mentioned in the timetable. Finally, the authors solved the problem by proposing a NSGA-II optimization technique. Liu and Ceder [139] studied the impact of schedule deviations on public transport users’ routing choices. They developed a collaborative approach for timetabling, vehicle scheduling, and demand assignment simultaneously. For the electric buses, Teng et al. [90] addressed the single-line bus timetabling and vehicle scheduling problem by proposing a multi-objective particle swarm optimization (PSO) algorithm. This paper aims to minimize the number of electric buses, and simultaneously, their charging cost.

Bi-level programming solves the problem in two different stages: leader and follower. Leaders optimize their objective regardless of followers’ objective; then, followers
the problem and optimize their objective function based on the output of the first stage optimization of leader. Liu and Ceder [140] proposed a bi-level integer programming model that considers the interests of public transport users and service providers to optimize the public transport timetable integrated with vehicle scheduling. A novel deficit function (DF)-based sequential search method is proposed to solve the problem and obtain Pareto fronts. Liu et al. [141] formulated an integer programming model to address integrated bus timetabling and vehicle scheduling. Their research aimed to minimize the number of vehicles required for the total trips and maximize the number of vehicles that arrived simultaneously at the transfer nodes. This bi-objective model was solved based on a two-stage deficit function approach to generate Pareto optimal fronts. It is worth mentioning that the last two papers showed how changes in bus timetable and even vehicle scheduling could affect passengers’ trip mode choice. Liu and Shen [142] presented a bi-level programming formulation to solve bus timetabling and vehicle scheduling. At the first level, the number of required vehicles to assign to each trip is minimized. Then, at the second level, passengers’ transfer time in connection stops is minimized concerning the solution from the first level.

The last strategy is reordering, which means considering public transportation planning as one integrated problem. Michaelis and Schöbel [143] considered four stages of a public transportation planning system as one integrated problem. The four stages were: network design (line planning), timetabling, vehicle scheduling, and crew scheduling. The authors proposed new order for the public transportation system planning. First, the vehicle routes are designed; in the second stage, the designed routes should be split into bus lines; and in the final stage, a periodic timetable should be assigned for each line. Pätzold et al. [144] proposed three ways to include VS in different planning stages of public transportation systems, such as timetabling and line planning. The research aimed to consider three ways to “look ahead” of planning to decrease operational costs. The complete integration of electric bus scheduling and crew scheduling was studied by Perumal et al. [145]. The column-generation method was used to find the best vehicle and crew schedule regarding operational costs. Table 6 represents an overview of the objective functions of various studies on bus scheduling and timetabling. This table shows the potential research areas for future studies regarding simultaneous optimization of bus scheduling and timetabling objectives. Additionally, we can conclude that there is a significant lack of research on integrating electric bus scheduling and charging TOU and combined optimization of EBS and timetabling. Table 7 represents the method and algorithms adopted to solve electric bus scheduling and timetabling problems. The table shows that the number of studies using exact solution methods is remarkably less than the number papers using heuristic or metaheuristic solution approaches. Although EBS with multiple depots is an NP-hard problem, there is a research gap in reformulating such problems and solving them by the exact methods. Table 8 shows the advantages and disadvantages of methods used for the bus scheduling and timetabling and the accuracy of the results obtained by such methods.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Electric Bus</th>
<th>VS</th>
<th>TT</th>
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<tr>
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<td>Wen et al. (2016) [102]</td>
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Table 6. Different studies related to the objectives of bus scheduling and timetabling.
### Table 6. Cont.

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<tr>
<td>Cao &amp; Ceder (2019)</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Zhang et al. (2020)</td>
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</table>

### Table 7. The characteristics of electric bus scheduling, timetabling, and solution approaches.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Single/Multi Depot</th>
<th>Single/Multi Line</th>
<th>Vehicle Type</th>
<th>Model</th>
<th>Method/Algorithm</th>
<th>Case Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ibarra-Rojas et al. (2014)</td>
<td>Single</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>$\epsilon$-constraint</td>
<td>Monterrey, Mexico</td>
</tr>
<tr>
<td>Wen et al. (2016)</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MIP</td>
<td>Adaptive LNS</td>
<td>-</td>
</tr>
<tr>
<td>Fonseca et al. (2018)</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>Matheuristic</td>
<td>Copenhagen, Denmark</td>
</tr>
<tr>
<td>Li et al. (2019)</td>
<td>Multi</td>
<td>Multi</td>
<td>Heterogeneous</td>
<td>ILP</td>
<td>Time-space-energy network and time-space</td>
<td>Hong Kong</td>
</tr>
</tbody>
</table>
Table 7. Cont.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Single/Multi Depot</th>
<th>Single/Multi Line</th>
<th>Vehicle Type</th>
<th>Model</th>
<th>Method/Algorithm</th>
<th>Case Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhang et al. (2020) [91]</td>
<td>Single</td>
<td>Single</td>
<td>Heterogeneous</td>
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<td>GA</td>
<td>Beijing, China</td>
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<td>Yao et al. (2020) [116]</td>
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<td>Multi</td>
<td>Heterogeneous</td>
<td>MILP</td>
<td>GA</td>
<td>Beijing, China</td>
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<td>Teng et al. (2020) [90]</td>
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<td>Single</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>Multiobjective PSO</td>
<td>Shanghai, China</td>
</tr>
<tr>
<td>Zhou et al. (2020) [117]</td>
<td>Single</td>
<td>Multi</td>
<td>Heterogeneous</td>
<td>Bi-level programming</td>
<td>Iterative neighborhood search</td>
<td>Beijing, China</td>
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<td></td>
</tr>
<tr>
<td>Liu &amp; Ceder (2020) [87]</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>DF and IP</td>
<td>Adjusted max-flow</td>
<td>Singapore</td>
</tr>
<tr>
<td>Li et al. (2020) [114]</td>
<td>Single</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>Nonconvex mathematical model</td>
<td>AGA</td>
<td>Anting Town, Shanghai</td>
</tr>
<tr>
<td>Sung et al. (2022) [111]</td>
<td>Multi</td>
<td>Multi</td>
<td>Heterogeneous</td>
<td>Simulation</td>
<td>Hueristic</td>
<td>Kaohsiung, Taiwan</td>
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<td>Gkiotsalitis [123]</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>Branch-and-cut</td>
<td>-</td>
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<tr>
<td>Wang et al. (2022) [88]</td>
<td>Single</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>MILP</td>
<td>Oslo, Norway</td>
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<tr>
<td>Jiang &amp; Zhang (2022) [82]</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>Branch-and-price</td>
<td>-</td>
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<tr>
<td>Zhang et al. (2022) [125]</td>
<td>Multi</td>
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<td>Heterogeneous</td>
<td>MILP</td>
<td>ALNS</td>
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<tr>
<td>Guo et al. (2022) [115]</td>
<td>Single</td>
<td>Single</td>
<td>Homogeneous</td>
<td>UBPM</td>
<td>GA</td>
<td>Nanchang, China</td>
</tr>
<tr>
<td>Wu et al. (2022) [126]</td>
<td>Multi</td>
<td>Multi</td>
<td>Homogeneous</td>
<td>MILP</td>
<td>Branch-and-price</td>
<td>Guangzhou, China</td>
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Table 8. Comparison of the different studies in terms of accuracy and solution approach.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Method</th>
<th>Gap</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ibarra-Rojas et al. (2014) [137]</td>
<td>$\epsilon$-constraint</td>
<td>0 (for up to 50 bus lines)</td>
<td>Allows to analyze the trade-off between level of service and number of buses.</td>
<td>Limit to solve small and medium size problems</td>
</tr>
<tr>
<td>Schmid &amp; Ehmke (2015) [136]</td>
<td>LNS</td>
<td>21.68%</td>
<td>able to outperform a commercial solver in terms of run time and solution quality</td>
<td>Solutions are far from optimum for large-scale problems</td>
</tr>
<tr>
<td>Wen et al. (2016) [102]</td>
<td>Adaptive LNS</td>
<td>4.4%</td>
<td>Provide good solutions for large instances and near optimum solutions for small instances</td>
<td>Large fluctuation for different instances</td>
</tr>
<tr>
<td>Fonseca et al. (2018) [132]</td>
<td>Matheuristic</td>
<td>9.72%</td>
<td>Able to find better feasible solutions faster than a commercial solver</td>
<td>Requires many analysis to choose the right parameters</td>
</tr>
<tr>
<td>Cao &amp; Ceder (2019) [146]</td>
<td>GA</td>
<td>0</td>
<td>Easy to implement</td>
<td>Only applies on one bus line and one vehicle type</td>
</tr>
<tr>
<td>Li et al. (2019) [74]</td>
<td>Time-space-energy network and time-space</td>
<td>3.19%</td>
<td>Simple implementation</td>
<td>Approximate solutions</td>
</tr>
<tr>
<td>Zhang et al. (2020) [91]</td>
<td>GA</td>
<td>5.8%</td>
<td>It can provide some quick and relatively inexpensive solutions</td>
<td>It reaches out of memory error after 15 min</td>
</tr>
<tr>
<td>Yao et al. (2020) [116]</td>
<td>GA</td>
<td>-1</td>
<td>Easy to understand and implement</td>
<td>Unable to find optimal solutions consistently</td>
</tr>
<tr>
<td>Teng et al. (2020) [90]</td>
<td>Multiobjective PSO</td>
<td>-</td>
<td>Robustness to control parameters</td>
<td>Converge to local solutions</td>
</tr>
<tr>
<td>Zhou et al. (2020) [117]</td>
<td>Iterative neighborhood search</td>
<td>-</td>
<td>Easy to code and use</td>
<td>Many parameters have to be tuned</td>
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<tr>
<td>Liu &amp; Ceder (2020) [87]</td>
<td>Adjusted max-flow</td>
<td>0</td>
<td>Could be applied to large-scale problems</td>
<td>High complexity</td>
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Table 8. Cont.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Method</th>
<th>Gap</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
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<tbody>
<tr>
<td>Li et al. (2020) [114]</td>
<td>AGA</td>
<td>-</td>
<td>Easy to understand</td>
<td>Solutions may be far from optimum</td>
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<td>Bie et al. (2021) [111]</td>
<td>Branch-and-price</td>
<td>0</td>
<td>Obtain the exact solution set</td>
<td>High complexity to develop</td>
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<td>Sung et al. (2022) [111]</td>
<td>Hueristic</td>
<td>-</td>
<td>Could be used for initial solution for other problems</td>
<td>Obtain local solutions</td>
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<td>Gkiotsalitis [123]</td>
<td>Branch-and-cut</td>
<td>0</td>
<td>Reliable and obtain the exact solution set</td>
<td>Limited to 30 number of trips</td>
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<td>Wang et al. (2022) [88]</td>
<td>MILP</td>
<td>4%</td>
<td>Can obtain the solution with high quality</td>
<td>Unable to find the optimum solution</td>
</tr>
<tr>
<td>Jiang &amp; Zhang (2022) [82]</td>
<td>Branch-and-price</td>
<td>0.32%</td>
<td>Able to generate high-quality solutions</td>
<td>Limited to instances with 400 trips</td>
</tr>
<tr>
<td>Zhang et al. (2022) [125]</td>
<td>ALNS</td>
<td>0.08%</td>
<td>Able to find high quality solutions</td>
<td>Requires many analysis to choose the right method</td>
</tr>
<tr>
<td>Guo et al. (2022) [115]</td>
<td>GA</td>
<td>-</td>
<td>Easy to understand</td>
<td>Computationally expensive</td>
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<tr>
<td>Wu et al. (2022) [126]</td>
<td>Branch-and-price</td>
<td>9.59%</td>
<td>More reliable and efficient</td>
<td>Limitation on the scalability of the method</td>
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</table>

1 Not mentioned.

3.5. Impact on The Power System

Electric buses present both challenges and opportunities for the future power network due to their size and flexibility. One such challenge is charging the electric buses’ batteries [147]. The primary attributes of EBs include a battery capacity greater than 200 kWh, charging power greater than 40 kW, and a driving range of 200 km [148]. Benefit-wise, EBs are superior to private EVs. They enable large passenger transfers, saving space on the road and using less energy. The basic structure of fast charging infrastructure for charging buses includes an AC/DC power converter, a transformer, a distribution grid, and its connection, as shown in Figure 5. Transformation from the conventional buses to electric buses will have a significant impact on the electric grid. An electric bus depot which has hundreds of buses will have a severe impact on the power grid [149]. Therefore, it is very high important for both the power utilities and transportation companies to quantify electric buses’ power demand and their impact on distribution grid. The power grid can face huge stress due to the uncoordinated charging of EBs [150]. On the other hand, coordinated charging can deliver excessive benefits, such as valley filling and peak clipping [151]. EVs for public transportation, such as electric buses, have received little attention so far. Due to their high-power consumption and rigorous charge times, EBs in particular present unique charging-related issues. Additionally, the battery capacities of EB used for public transportation are very high (150–450 kW), greater than that of electric cars, and the charging power is also several times greater than that of electric cars [152]. As a result, high energy consumption and detrimental effects on power distribution networks may result [153]. As electric transportation increases, the electricity demand required to charge their batteries will also increase.

3.5.1. Impact on the Distribution Grid

System security around the integration of EVs and EBs is receiving a lot of attention due to the high charging power of EVs and EBs. As a result, the majority of existing publications concentrate on the effective analyses of them on the distribution network. They consider the objective operations pertaining to system operation, such as power market participation [154], grid loss minimization [155], and network security [156]. The high penetration of electric transportation deployment can cause different problems in the power system, such as increased peak demand, voltage drops, degrading the power quality, blackouts, and power system losses, as shown in Figure 6. Leou and Hung [153] established a mathematical model and tested it for a small bus fleet of 10 buses in order
to take into account the charging scheduling of electric buses for the central depot. This strategy schedules bus charging based on time-of-use rates in an effort to reduce energy costs. The EB fleet’s impact on the grid’s charging, which results in overloading of the distribution transformer [157], and more crucially, the necessity for buses to wait until off-peak hours to be charged, was not considered by the author. In [158], the effects of the EB charging demand on the local grid and distribution were investigated on a substation in Warsaw, Poland. In [159], two case studies employing a technique for predicting the energy and charging needs of electrified public transit are reported. By analyzing their actual, comprehensive energy use, the authors of [160] proposed a battery-sizing methodology for several electric bus services. There are two ways to mitigate the impact of the increasing penetration of electric transportation on the power system. The first one is a direct approach, where the power system operator can directly control the charging and discharging of electric vehicles by using different charging algorithms [161]. Such a method will benefit the power system operation and the consumer. The second method is to indirectly control the charging and discharging behavior of the consumer using demand–response programs, such as time of use pricing or real-time pricing [162]. Such an approach will compel the consumer to use the off-peak hours to charge his electric vehicle by providing low prices for off-peak hours and high for peak hours. However, the second method might have a rebound peak if everyone uses a low pricing peak to charge their electric vehicles.

Figure 5. Representation of electric bus charging infrastructure’s connection with a power system.

Within a smart grid, EVs, including EBs, will use optimal charging scheduling for flattening the load profile of the electrical system [163]. In order to address the issue of coordinated charging over day-ahead scheduling, various mathematical models have been proposed and developed, such as linear and mixed-integer linear models, which focus on minimizing EV load deviation [164], total loss minimization [165], and charging cost minimization [166]. One study [167] used data gathered from automated vehicle location (AVL) in the BusGrid system to forecast future passenger demand at bus stops and in routes using supervised machine learning techniques. This improved the design of new routes and improved bus scheduling. BusGrid is an information system for enhancing customer satisfaction and productivity in public transportation bus services. BusGrid works with an operator to enhance bus timetables and develop new bus routes and stops based on anticipated demand by receiving and processing real-time data from sensors put on a bus fleet called AVL and automatic passenger counting (APC). A passenger-demand forecasting model created especially for bus networks is provided in [168]. In this study, a time-series forecasting method was used to present a weighted ensemble prediction model that correctly forecasts bus demand for a P-minute time window using data from two Poisson models and an auto-regressive integrated moving average (ARIMA) model. According to [169], AVL data were used with machine learning clustering techniques to improve the performance of the AVL system for determining bus schedules in Portugal. This connection made it easier to determine whether a schedule adjustment will satisfy the
needs of the network. In a different study [170], the authors proposed employing machine learning methods such as unsupervised clustering to identify trends among AVL data in order to enhance Sweden’s public transportation timetables. Other objectives have also been taken into account, including reducing the loss of electricity to the grid, EV battery degradation, reducing CO₂ emissions, and increasing the level of satisfaction among EV owners [171]. A new business paradigm is being facilitated by the rise in EVs and EBs, and the inclusion of renewable energy resources in the future power network [172]. For the introduction of EBs in power systems, several researchers created novel approaches with a variety of primary goals. Electric bus energy estimation has been studied by some writers. Stochastic modeling and forecasting of load demand of EB battery swap station are studied in [173]. Fuzzy clustering and least-squares support vector machines optimized by the Wolf pack method were used to forecast EB load over the short term [174]. The optimization of the EB aggregator will minimize charging costs while satisfying a variety of electrical constraints to optimize the charging load during the charging process. The optimization problem considering the minimizing the daily charging cost of EBs is as Appendix A.1 [148].

Thiringer and Haghbin [175] investigated the effect of EVs (including electric buses) on the substation reserves in order to address the power quality issue in a fast-charging station. The case study used in this work was based on real electric bus data from Gothenburg, Sweden. This study examined potential problems with the effect on the electrical system but did not make recommendations for how to improve the charging schedule. Zoltowska and Lin [176] used aggregated day-ahead auction bids to plan the charging schedule of EBs for minimizing the cost of charging scheduling. Using the market participation idea, an optimization model for coordinated charging of the bus fleet and fast-charging stations was created in this study. There are many optimization techniques for battery switching [177], and there is the flash wireless charging concept for bus timetables [178]. Different studies have evaluated the impact of electric transportation on the distribution voltage by implementing the optimal charging strategy with the operation constraint on the distribution network [179,180]. The author in [181] proposed the Monte Carlo approach to assess the effect of electric transportation charging on the voltage imbalance level and calculate the voltage quality. In [182], other factors of the distribution system, such as, but not limited to, feeder losses, variation in the load, and load factor, were analyzed with an optimal charging algorithm. In [183], the author compared the impacts of electric-vehicle charging on European and North American distribution systems. These voltage drops on the distribution system can be mitigated by installing an additional transformer, but it is expensive and needs infrastructural changes.

![Figure 6. Impact on the transformer and grid.](image)

### 3.5.2. Impact on the Transformer

Electricity is typically supplied via liquid-fill and dry-type transformers in distribution systems. The power rating of such a transformer often varies by country, ranging from a few kVA to hundreds of thousands of kVA. For instance, the power rating utilized on 11 and 22 kV networks in Australia ranges from 10 to 2500 kVA [184]. The price of a transformer varies from hundreds of dollars to several hundred thousand dollars depending on the brand, quality, size, and kind. According to [185], EVs are not taken into account while sizing distribution...
transformers in conventional power systems. As the penetration of EVs rises, the demand on the transformers will peak as a result of charging such a large battery bank. It will result in extreme voltage drops, increased power losses, and a shorter lifespan for the transformers.

Due to the existence of EBs uncoordinated charging, distribution system operators and transmission system operators (TSO) may experience difficulties in the future. All of these issues must be handled by DSO and TSO using all of the resources at their disposal. The EV aggregator is now a required partner who gives the DSO and TSO technical services [186]. The aggregator will serve as a middleman between operators, who will likely make use of market mechanisms to acquire the required assets and EB stations. Such an aggregator can be implemented on the distribution transformer, as distribution transformers are susceptible and costly devices in the distribution system. This will also help the distribution transformer to reduce losses and damage cost due to peak load of buses. The EB aggregator transformer will provide its services to TSO and DSO for grid operations, and maybe to other electricity partners to optimize their energy portfolio purchases. According to a survey, the most significant share in the distribution network is the new installation of the distribution transformer [187]. The peak demand on the transformer side will indirectly raise the temperature that causes the so-called accelerated ageing of the transformer insulation as the penetration level of electric vehicles rises [188]. Such an aging effect may cost billions of dollars to the power system utilities [189]. Ahmadian et al. [190] studied the effect of EV charging on the traditional system, which results in voltage profile violation. The authors ideally distributed and designed the shunt capacitor and the wind-based distributed generation (DG) across the system, considering the load variability of the EVs and DGs in relation to the system voltage profile. They also used a short-schedule decision for the load tap changer (LTC) tap setting of the transformer. Azzouz et al. [191] took into account the high penetration of EVs and DGs in an attempt to reduce voltage variation and LTC tap operation, maximize the EVs delivered power, and optimize the power captured by the DGs. The high penetration level of the electric transportation (specifically electric buses) will cause problems on the transformer, including but not limited to decreasing the lifetime of transformer, overloading the transformer, and increase power losses on the transformer, as shown in Figure 6 [192].

It is now understood that if the high penetration of electrification of the transport system is not correctly managed, it will cause a severe impact on the distribution system and grid side.

### 3.5.3. Ancillary Service by Electric Buses

According to [193], uncoordinated charging overloads the transformer and transmission line. EB charging can be categorized as unidirectional or bidirectional depending on the direction of the energy flow [194]. In unidirectional charging, power is sent from the grid to the EB acting as a load in the power system. The control of EV charging during unidirectional and controlled charging should aim to reduce peak demand. A bidirectional AC/DC converter is used by EVs to support energy transfer between the grid and the vehicle in both directions. There are two types of bi-directional power flow, that is, grid-to-vehicle (G2V), in which power is sent to the EV, and vehicle-to-grid (V2G) and vehicle-to-home (V2H), in which the EV serves as an ESS and feeds power into the grid [195]. Controlled and uncontrolled charging are further categories. The uncontrolled charging is done improperly and without the use of any control optimization techniques, which results in supply and demand imbalances, undesirable and unexpected peaks on the distribution system, increased voltage deviations, increased power losses, and decreased reserve margins [196]. In several studies, the V2G mode was taken into account, which is described as the EV’s capability to charge its batteries and give electricity to the grid, resulting in a bidirectional flow between the grid and the EV [197]. As shown in Figure 7, EBs can offer ancillary services to the power grid using various modes of operation, for instance, by improving grid quality through increasing the stability and generation dispatch. Providing improved energy management is also important, and can be accomplished through such things as peak shaving, reducing operation losses, and minimizing the cost. Such ancillary services also improve and regulate
the voltage and frequency of the distribution network. The bank of batteries can also provide active power to the grid. The authors of [198] suggest intelligently charged electrified transit by taking into account V2G for EBs to assist renewable energy sources in the Austin power grid. Reference [199] proposed a charging approach for quick-charging stations that was based on a decision-making procedure and held the stance that the EBs only paid under the quick-charger load limit. The best location for fast-charging stations with an energy storage system to maximize the financial advantages was investigated in [200,201]. The authors of [202] investigated multi-external aspects in EB scheduling.

![Figure 7. Ancillary services provided by EBs.](image)

Even if EVs improve the grid in a variety of ways, if the penetration level rises significantly, this negatively impacts the distribution transformer and distribution system. The bidirectional charger consumes EV load, which introduces harmonics into the system and degrades the power quality. Additionally, significant upgrading of the current communication and distribution networks is required for the adoption of a bidirectional charger. On the other hand, it is still challenging to assess how much EVs actually participate in electricity markets. It is challenging to assume these activities for EBs given the economic viability of V2G mode. Additionally, due to driving schedules, EBs are less flexible than light EVs. However, given their limited number, high charging power rate, and ability to charge in public locations, EBs are more easily aggregated.

In a nutshell, it is acknowledged that substantial EB implementation across the distribution system can dramatically increase load demand if EB charging and discharging infrastructure is not handled effectively. It will result in the grid's generational capacity being increased.

4. Challenges and Limitations

Implementing a fully electric bus transit system involves several challenges. The first challenge is the energy power supply issue of the high energy demand of electric buses, especially in big cities. Not all cities benefit from renewable energy sources for generating electricity; thus, satisfying the energy demand of a fully electric bus transportation system will be a big challenge for the energy side. Another challenge is the high purchasing price of fully electric buses compared to conventional or hybrid ones. Convincing cities' authorities, municipalities, and governments to switch to such a high-cost transit system is complicated, and that is why many cities have not decided to use electric buses. Last but not least is the range limitation of EBs, and researchers are trying to solve this issue by proposing different charging technologies or producing buses with longer travel ranges. However,
such solutions are costly for transit agencies. Thus, still, there is a vast amount of research to be done to address this problem more sustainably.

Another group of challenges are operational-planning challenges. This group relates to the recharging duration, battery degradation, and low efficiency of pantograph chargers. The refueling process of conventional buses does not take long and can be done every hour. The electric bus recharging process is a long-lasting task that should be done during off-peak hours to balance the load on the distribution grid. EB batteries will degrade slowly over time, depending on the frequency and type of charging used. Electric bus batteries are considered to have reached their end of life at 80% capacity or when they lose 5% of their charge per hour without use. Generally, EB batteries are warranted for 8–12 years. This lifetime is much less than that of traditional buses. Cold temperatures will affect battery charge primarily due to the use of heating, which greatly impacts the amount of charge used, reducing range by up to 41%. Therefore, charge needs to be maintained above 20% to reduce the risk of stalling in the winter.

Switching from a conventional bus system to a wholly electric one for cities lacking the required infrastructure is very complicated. On the other hand, integrating bus depot operators and energy sectors may be feasible for only small towns trying to improve or design a new transit system while considering the impact of charger loads on the grid. That is because managing and optimizing the combination of transit authorities and energy manager agencies for big cities is complex. Moreover, the impact of installing pantograph chargers in the neighborhood is a challenge for transit authorities and urban planners. Safety is another challenging issue with using high voltage chargers for EBs. Although there is no report regarding the injuries or deaths related to charging infrastructure’s low safety measures, such infrastructure should be examined and checked regularly to reduce the risk as much as possible.

The electricity generation finite capacity is an important factor preventing distribution of electric buses in cities around the world. The power generators might not be able to meet the demand of a fully electric transit system, and transforming from the oil-based system to an electricity-based system would take time. This is the reason that most cities will switch from conventional buses to electric ones gradually. In many cases, transit authorities have decided to use hybrid buses as a first step and then gradually replace them with electric ones.

The accelerated deployment of EBs will place a heavy load on the grid, affecting the operation of utilities and power systems. Public transit operators typically lack the infrastructure required to address such a problem. Extending the distribution system’s capacity is possible, although doing so would be expensive and take a long time to complete. Therefore, creating innovative methods to reduce severe grid stress by fleet charging is a crucial problem [58,149,203]. Smart coordinated charging techniques should be regarded as one of the most important aims to be handled for this goal. In addition, public transit authorities must consider how the grid and bus systems interact. The best strategies for dealing with hierarchical decisions and decisions containing various and competing factors to optimize are bi-level and multi-objective optimization. Another attractive study area is the subject of bus to grid (B2G) interactions. For example, public transport authorities can sell energy back to the grid by taking advantage of intra-day changes in the price of electricity.

5. Future Direction

We divided the literature gaps in electric bus operation planning into three categories: electric bus scheduling and timetabling, fast charging infrastructure location planning, and impacts on the grid.

Although electric bus scheduling, timetabling, and the charging station location problem have been the subjects of various studies, more work is still needed to bridge the gap between theory and practice. If we explore the literature, we can find that only a few works have been done on the influence of electric bus scheduling on the location of fast charging infrastructure and vice versa. A few papers currently deal with the location problem of fast
charging infrastructures. According to these papers, the charging station location problem is treated as an individual optimization problem.

To the best of our knowledge, there are very few studies on rescheduling and planning robustness for scheduling electric buses in the literature. Thus, future research is expected to focus on the design of recovery techniques that facilitate the use of electric buses. The integration of public transit operation planning steps for electric buses has not been investigated comprehensively and deeply in the literature. Although considering joint optimization of planning problems would increase the computational complexity, it may improve the efficiency and level of service of EBs transit systems. Therefore, such integration could be an interesting area of research in the future.

Charging scheduling of electric buses should be studied for heterogeneous bus types with mixed-type charging technology, such as depot charging and fast charging. Additionally, to dynamically modify the charging schedule, monitoring the real-time information of EBs, such as state of charge (SoC) of batteries, traffic conditions, the passenger travel demand during the day, and buses’ earliness and tardiness, should be considered in future works [72]. Moreover, the stochastic behavior of electric bus operations has not been well examined up to this point. As a result, using stochastic or robust optimization models seems to be a promising area for further research [68].

Another gap that should be filled is the impacts of charging station location and electric bus scheduling on the grid. If we want to categorize such impacts, it will result in negative and positive impacts. Negative impacts refer to the charging loads of electric buses, especially during peak hours. Reducing the grid’s stability, generating harmonics, and reducing the transformer service life are several negative impacts on the grid. Such issues should be addressed in future studies, and the effects of the EBs charging load should be taken into account for each step of public transportation planning. The positive side refers to using V2G, or in this context, B2G configuration. This technology will help the grid to be more stable and supply energy through ancillary services.

In most studies, the charging locations of electric buses are assumed to be at depots or terminals [61]. By eliminating this assumption, the location problem for charging stations could be studied too. With a rapid increase in fully electric buses, research on the integration of bus scheduling and fast-charging infrastructure location problem will be necessary. Integration of crew scheduling with electric bus scheduling and timetabling has significant research value and should be considered in future studies.

In a real-world setting, unpredictable circumstances, including road, weather conditions, and driving habits, may impact how much energy BEBs use [204]. Additionally, estimating EBs’ energy consumption involves an unanticipated inaccuracy due to the uncertainty around passenger volume. This would affect the scheduling process of EBs and their recharging procedure. Thus, the uncertain energy consumption of EBs and more accurate energy consumption models should be taken into account to improve bus scheduling and their charging scheduling. Adding more charging strategies and partial charging choices might further boost the BEB system’s operating effectiveness. As a result, future studies could investigate a hybrid strategy that combines various charging techniques and further look into the possibility of partial charging at the central terminal in mixed-type chargers.

Exploring the effects of charger location planning for expanding or modifying the network design should be a focus. In other words, the impacts of fast charging infrastructure locations should also be taken into account from the bus network design point of view. Furthermore, operational features such as traffic conditions, energy consumption, charging schedules, and time-of-use pricing strategy could be considered in future research [76].

All in all, Figure 8 represents different solution approaches to deal with electric bus scheduling, timetabling, charging scheduling, fast charging infrastructure location planning, and their impacts on the grid. The red dots indicate that the integration of these research areas has not been studied yet. Note that several other possibilities for integrating these problems are not shown in this figure and have not been investigated. The main purpose of this figure is to show the adopted methods for solving the integration of such problems.
with each other. As it is represented in the figure, a few papers discussed such optimization problems with exact solution approaches. Thus, focusing on developing exact methods to solve these problems would be another research goal for future studies. Another point of this figure is to show the possible future direction for research in this scope. For example, electric bus scheduling, FCILP, and impacts on the grid have not been investigated yet. Thus, this could be an interesting area of research in the future.

Figure 8. Integration of EB optimization problems and possibilities of future studies.

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Abbreviations
The following abbreviations are used in this manuscript:

AARC  Affinely adjustable robust counterpart
ACO  Ant colony optimization
AGA  Adaptive genetic algorithm
BEB  Battery-electric bus
BOT Build-operate-transfer
BPSO Binary particle swarm optimization
B2G Bus to grid
DF Deficit function
DG Distribution grid
DOD Depth of discharge
DSO Distribution system operation
EB Electric bus
EBs Electric bus scheduling
EHDG Enhanced heuristic descent gradient
EV Electric vehicle
EBS Electric bus scheduling
FCILP Fast charging infrastructure location planning
GA Genetic algorithm
G2V Grid to vehicle
ILP Integer linear programming
ITTVS Integrated timetabling and vehicle scheduling
LNS Large neighborhood search
MILP Mixed-integer linear programming
MIP Mixed-integer programming
NSGA-II Non-dominated sorting genetic algorithm II
PHA Progressive hedging algorithm
PHEV Plug-in hybrid electric vehicles
PSO Particle swarm optimization
SA Simulated annealing
TOU Time-of-use
TSO Transmission system operation
TT Timetabling
UBPM Uncertain bi-level programming model
VS Vehicle scheduling
VNS Variable neighborhood search
VSP-TW Vehicle scheduling problem with time windows
V2G Vehicle to grid
V2H Vehicle to home

Appendix A

Appendix A.1

\[
\min C^{EB} = \min \left( C_p + \sum_{t=1}^{D} \pi_t \cdot P_t^{EB} \right) \quad (A1)
\]

The objective function aims to minimize the penalty cost for the aggregated EB is \( C_p \) and summation of the electricity cost at time interval \( t \), and the charging load for all the EBs at each time interval \( t \) is \( P_t^{EB} \). The optimal power flow is a combination of the operation constraints and objective function, as mentioned in Equations (A1)–(A10). The power flow equation is subjected to the active and reactive power balance equations as follows:

\[
P_{j,t}^g - P_{j,t}^d = \sum_{k=1}^{N} V_{j,t} \cdot V_{k,t} \cdot Y_{j,k} \cdot \cos \left( \theta_{j,k} + \delta_{k,t} - \delta_{j,t} \right), \quad \forall t \in T; \quad \forall (j,k) \in N \quad (A2)
\]

\[
Q_{j,t}^g - Q_{j,t}^d = -\sum_{k=1}^{N} V_{j,t} \cdot V_{k,t} \cdot Y_{j,k} \cdot \sin \left( \theta_{j,k} + \delta_{k,t} - \delta_{j,t} \right), \quad \forall t \in T; \forall (j,k) \in N \quad (A3)
\]

where \( j, k, P_{j,t}, P_{k,t}, V_{j,t}, V_{k,t}, \theta_{j,k}, \delta_{k,t}, \delta_{j,t}, Q_{j,t}^g, \) and \( Q_{j,t}^d \) are bus \( j \) and \( k \), active power generation, active power demand, voltage at bus \( j \), \( k \) at time \( t \), voltage angle at bus \( j \), \( k \) at time \( t \), reactive power generation, and reactive power demand, respectively. Equation (A2) is the active power flow equation, where the first term is active power generation of the distribution substation. The second term is the aggregated active power demand of the
EB and household connected to that bus. The right-hand sides of the equations in (A2) represent the active power losses at that bus. Equation (A3) is the reactive power flow equation, where the first term is reactive power generation of the distribution substation. The second term is the aggregated reactive power demand. The right-hand sides of the equations in (A3) represent the active power losses at that bus.

Other constraints of the optimal power flow are voltage of the bus, angle of the bus, and active and reactive power generation limit. Equation (A4) ensures that the bus voltage is within the limit. Additionally, Equation (A5) keeps the bus angle between the required limits. Similarly, the active and reactive power drawn from the substation are limited in the equation as in (A6) and (A7), respectively.

\[
V_{\text{in}}^\text{min} \leq V_{\text{j},t} \leq V_{\text{j},t}^\text{max}, \quad \forall t \in T; \forall j \in N
\]  
(A4)

\[
\sigma_{\text{j},t}^\text{min} \leq \sigma_{\text{j},t} \leq \sigma_{\text{j},t}^\text{max}, \quad \forall t \in T; \forall j \in N
\]  
(A5)

\[
p_{\text{j},t}^\text{min} \leq p_{\text{j},t} \leq p_{\text{j},t}^\text{max}, \quad \forall t \in T; \forall j = s
\]  
(A6)

\[
Q_{\text{j},t}^\text{min} \leq Q_{\text{j},t} \leq Q_{\text{j},t}^\text{max}, \quad \forall t \in T; \forall j = s
\]  
(A7)

where \(V_{\text{in}}^\text{min}, V_{\text{in}}^\text{max}, \sigma_{\text{j},t}^\text{min}, \sigma_{\text{j},t}^\text{max}, p_{\text{j},t}^\text{min}, p_{\text{j},t}^\text{max}, Q_{\text{j},t}^\text{min},\) and \(Q_{\text{j},t}^\text{max}\) are the minimum and maximum voltage, voltage angle, and minimum and maximum active and reactive generation power limits of the substation, respectively. The power flow equation includes other additional constraints of EB charging and power/energy requirements. The energy required for charging all the EBS is guaranteed in (A8), and the charging power of EB should not exceed the maximum power limit of the distribution system operators (DSO), as in (A9). Equation (A10) ensures that the charging power of the EB is within the limit of the charging power of the charger.

\[
E_{\text{i},t}^\text{req} = \sum_{l=1}^{D} p_{\text{i},l}^\text{Ch} \cdot \Delta T, \quad \forall t \in T
\]  
(A8)

\[
p_{\text{i},t}^\text{EB} < p_{\text{i},t}^\text{max}_{\text{DSO}}, \quad \forall t \in T
\]  
(A9)

\[
0 \leq p_{\text{i},t}^\text{EB} \leq p_{\text{i},t}^\text{max}_{\text{Ch}}, \quad \forall t \in T
\]  
(A10)

where \(E_{\text{i},t}^\text{req}, p_{\text{i},l}^\text{Ch}, p_{\text{i},t}^\text{EB}, p_{\text{i},t}^\text{max}_{\text{DSO}},\) and \(p_{\text{i},t}^\text{max}_{\text{Ch}}\) are the energy required for the EB, charging power of EB, maximum power drawn from the DSO, and maximum power limit on the EB’s charging.

Appendix A.2

\[
\text{Minimize} \quad \sum_{o \in O} c_o \cdot x_0
\]  
(A11)

subject to

\[
y_{\text{i},t}^\text{charging} \leq \sigma \cdot x_0 \quad \forall l \in L
\]  
(A12)

\[
y_{\text{l},t}^\text{charging} = 1 \quad \forall 0 \in O_l, l \in L
\]  
(A13)

\[
y_{\text{l},t}^\text{charging} = c \quad \forall 0 \in O_l, l \in L
\]  
(A14)

\[
y_{\text{i},t}^\text{charging} + y_{\text{i},t}^\text{charging} = y_{\text{i},t}^\text{charging} \quad \forall 0 \in O_l, l \in L
\]  
(A15)

\[
y_{\text{i},t}^\text{charging} = y_{\text{i},t}^\text{charging} - R_{\text{i},t}\quad \forall 0 \in O_l, l \in L
\]  
(A16)

\[
y_{\text{i},t}^\text{charging} \geq R_{\text{i},t} \cdot (1 + \text{SOC}_{\text{min}}) \quad \forall l \in L
\]  
(A17)

\[
y_{\text{i},t}^\text{charging} = y_{\text{i},t}^\text{charging} \quad \forall 0 \in O_l, l \in L
\]  
(A18)

\[
x_0 \in \{0, 1\} \quad 0 \in O
\]  
(A19)

\[
y_{\text{i},t}^\text{charging}, y_{\text{i},t}^\text{charging}, y_{\text{i},t}^\text{charging} \in \mathbb{Z}^+ \quad 0 \in O_l, l \in L
\]  
(A20)
The objective function in (A11) is to reduce the overall cost of installing chargers. Constraints (A12), which prevent the energy delivered from the charging station from going over the maximum battery capacity, are in place. The energy level is initialized by constraints (A13) at all line starts and ends. The energy is balanced at each bus stop along a line thanks to constraints (A14). It suggests that the amount of energy in the bus’s battery when it leaves a bus stop is equal to the total of the energy it had when it arrived at the stop and the energy it received from charging. According to Equation (A15), the amount of energy in the battery when the bus enters the middle stop along a line is equal to the amount of energy in the battery when the bus leaves the prior bus stop, less the amount of energy used while traveling. Equation (A16) makes sure that while moving from one stop to another, the energy level does not fall below the minimal state-of-charge. Since there is no more distance to be covered, it is considered that no charging is necessary at line end stops. In (A17), there is support for this assumption.

**Appendix A.3**

\[
\min \sum_{i, (j, i) \in A} c_{ji} x_{ji} \quad (A21)
\]

\[
\text{s.t.} \sum_{j, (j, i) \in A} x_{ji} = 1 \quad \forall i \in S, \quad (A22)
\]

\[
\sum_{j, (j, i) \in A} x_{ji} - \sum_{i, (i, j) \in A} x_{ij} = 0 \quad \forall j \in S, \quad (A23)
\]

\[
g_i = \sum_{j, (j, i) \in A} (g_j + d_{ji}) x_{ji} \quad \forall i \in S, \quad (A24)
\]

\[
g_o = 0, \quad (A25)
\]

\[
(g_j + d_{jd}) x_{jd} \leq D \quad \forall (j, d) \in A, \quad (A26)
\]

\[
\sum_{i, (i, j) \in A} x_{ij} \leq K \quad j = 0, \quad (A27)
\]

\[
x_{ij} \in \{0, 1\} \quad (i, j) \in A. \quad (A28)
\]

Minimizing total operational costs is the objective. In terms of covering and flow conservation, constraints (A21) and (A22) are used. The cumulative distance traveled since the most recent battery renewal is determined in (A23). Equation (A24) ensures that a vehicle departs from the depot or completes the battery servicing at a station. Equation (A25) ensures the maximum route distance restriction cannot be exceeded. Constraints (A26) ensure that the overall fleet size does not exceed the upper bound.

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