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Optimal Design of Electric Bus Transport Systems With Minimal Total Ownership Cost

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ABSTRACT In this work, a generalized mathematical formulation is proposed to model a generic public transport system, and a mixed-integer linear programming (MILP) optimization is used to determine the optimal design of the system in terms of charging infrastructure deployment (with on-route and off-route charging), battery sizing, and charging schedules for each route in the network. Three case studies are used to validate the proposed model while demonstrating its universal applicability. First, the design of three individual routes with different characteristics is demonstrated. Then, a large-scale generic transport system with 180 routes, consisting of urban and suburban routes with varying characteristics is considered and the optimal design is obtained. Afterwards, the use of the proposed model for a long-term transport system planning problem is demonstrated by adapting the system to a 2030 scenario based on forecasted technological advancements. The proposed formulation is shown to be highly versatile in modeling a wide variety of components in an electric bus (EB) transport system and in achieving an optimal design with minimal TOC.

INDEX TERMS Electric buses, mixed-integer linear programming, charging infrastructure.

NOMENCLATURE

A. ACRONYMS

AML	Algebraic Modeling System
CC	City Center
DC	Depot Charger
DER	Distributed Energy Resource
EB	Electric Bus
ESS	Energy Storage System
EV	Electric Vehicle
FC	Flash Charger
FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
HF	High Frequency
LD	Long Distance
LF	Low Frequency
LV	Low Voltage
MD	Medium Distance
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
MPC	Model Predictive Control
MV	Medium Voltage
NLP	Non-Linear Programming
SD	Short Distance
SoC	State-of-Charge
SU	Suburban
TC	Terminal Charger
TOC	Total Ownership Cost

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B. SETS AND INDICES

i	Index for stops.
j	Index for trips.
k	Index for buses.
r	Index for routes.

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1	Index of the first element in a set.
end	Index of the last element in a set.
I^r	Set of all stops in route r.
J^r	Set of all trips in route r.
K^r	Set of all buses in route r.
R	Set of all routes.
H	Set of all available on-route charger types.

C. VARIABLES AND PARAMETERS

d_r^s	Average daily distance driven on route r.
L_r	Length of route r.
N_r^s	Number of stops in route r.
d_r^d	Average distance between stops on route r.
H_r	Operating hours of route r (time difference between first and last bus of the day)
T_r	Average duration of route r.
N_r^t	Daily number of trips for route r.
TOC	Total annual ownership cost of all routes.
C_r^{depot}	Total annual cost of all depot chargers in route r.
$C_r^{batteries}$	Total annual cost of all batteries in route r.
$C_r^{chargers}$	Total annual cost of all chargers in route r.
$C_r^{onroute}$	Total annual cost of batteries in route r.
$C_r^{offroute}$	Total annual cost of off-route charging in route r.
d_r	Binary variable indicating depot existence in route r.
C^d	Annual ownership cost of a depot charger.
$b_{k,r}$	Capacity of battery on bus k on route r.
C^B	Annual ownership cost of batteries, per kWh.
$x_{i,h,r}$	Binary variable indicating presence of on-route charger type h, at stop i, in route r
C_h^C	Annual ownership cost of on-route charger type h.
$e_{i,j,r}$	Energy charged at stop i, during trip j, in route r.
$C_{i,j,r}^E$	Energy cost per unit at stop i during trip j, in route r.
d_{year}	Number of days in a year.
n_r^{bus}	Number of buses deployed to route r.
F_r^b	Frequency of buses is route r.
$E_{i,j,k,r}$	Battery SoC at stop i during trip j, on bus k, in route r.
$\bar{B}$	Upper bound for the batteries' SoC.
$\underline{B}$	Lower bound for the batteries' SoC.
$\overline{E}_h$	Maximum charge capacity of onroute charger type h.
$\overline{E}_{DC}$	Maximum charge capacity of the depot charger.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The transport sector is simultaneously a major greenhouse gas emitter [1] and energy consumer worldwide, with its share of global energy consumption reaching a record high in 2019 [2]. With the increasing popularity of electric vehicles (EVs) as a highly versatile distributed energy resource (DER), the transport sector becomes a strategic priority in energy systems research and development. There have been numerous research studies aiming at harnessing the benefits of consumer-owned EVs for modern smart grids (SGs) through the use of modern control strategies [3]–[5]. Electric buses (EBs) seem to be less often investigated, which can be used to bring about techno-economic benefits in SG operation if optimized [6], [7].

In the context of public transport systems, the transition to a fully electric fleet is quite easy to carry out for three main reasons: First, due to heavy usage, public transport buses are frequently replaced and thus EBs can gradually replace conventional buses in the fleet without causing any interruption. Second, public transportation schedules are largely fixed (on the short-to-medium term), and thus individual upgrades to EBs can be seamlessly performed. Third, investment stability is mostly guaranteed in the public transportation sector, which facilitates the acquisition of new EB technologies [8]. In addition to the aforementioned facts, EB fleets have been shown to have a lower total ownership cost (TOC) compared to their conventional counterparts [9].

With all this being said, the main challenge hindering the transition thereto is the complexity involving designing an optimal charging infrastructure which meets the needs of the transport system and adheres to techno-economic constraints while maintaining the minimal TOC of the system [8]. With this being the primary motivation behind this work, a survey or recent scientific literature has been performed to identify the state-of-the-art progress on this topic.

B. STATE-OF-THE-ART SURVEY

In a recent study [10], the design of an EB transport system was optimized in terms of the fleet size and mix (with specifications of different bus types), and the charging infrastructure. The study identified that range limitation is indeed a main hurdle in electrification of public transport systems and that optimal design thereof is of paramount importance. By modeling the transport network of two European cities, a genetic algorithm (GA) was used obtain the optimal mix of EB models and the required number of each. The objective function of the GA was formulated as the TOC.

The authors in [11] used an enhanced GA algorithm combined with a departure time adjustment procedure to optimize EB deployment scheduling for a given bus route. The proposed model was applied to a bus route from a real-world public transit system in Nanjing, China. The results of the study showed that by applying the proposed model to optimize EB deployment and scheduling on that route, the operating costs are decreased due to the reduced number of deployed buses and drivers, as compared to experience-based scheduling used in the real-world scenario.

Another study [12] utilized a GA as an optimization approach for EB-based public transport systems. A real-world transit network in China was modeled, and the objective was to determine the optimal EB scheduling and charging infrastructure in order to meet the (constraint) scheduled routes with minimal charging costs. A sensitivity analysis

TABLE 1. A synopsis of recently published studies addressing the optimization of EB public transportation networks.

Reference	Computational Model	Charging Infrastructure	Charging Schedule	Routes	Battery Capacity	Bus Deployment
[11]	**GA**	Constraint	Constraint	Constraint	Constraint	**Decision Variable**
[12]	**GA**	Constraint	**Decision Variable**	Constraint	Constraint	**Decision Variable**
[13]	**NLP**	Constraint	**Decision Variable**	Constraint	Constraint	Constraint
[14]	**FLC**	Constraint	**Decision Variable**	Constraint	Constraint	Constraint
[15]	**MILP**	**Decision Variable**	Constraint	Constraint	**Decision Variable**	Constraint
[16]	**MIP**	**Decision Variable**	Constraint	Constraint	Constraint	Constraint

was used to assess the economic viability of the charging power and discharging depth (direct functions of charging infrastructure and EB schedules, respectively).

In [13], the target of the study was to evaluate the interaction between EB public transportation networks and the electrical grid, in the presence of dynamic pricing. A non-linear programming (NLP) model was used to determine the optimal charging schedule for EBs of eight EB routes in Shenzhen, China. The proposed optimization framework was employed to determine the charging schedules which would provide a tradeoff between meeting the transportation network constraints and minimizing the power grid congestions.

Similarly, [14] aimed at optimizing the power exchange between the public transport network and the power grid through the use of fuzzy logic control (FLC) to control the energy flow between the charging infrastructure and the EBs in the predefined transport network. The proposed model was used to perform simulations based on EB routes in Assam, India, and was shown to improve the voltage profile of the power grid while adhering to the transport network requirements and route schedules.

While the main focus of some studies was optimizing the EB schedules, others were concerned with optimizing the charging infrastructure, given a specified EB fleet. The previous studies [10], [12], like many others, considered only the presence of a charger at the EB depot, meaning they to return to the original depot in order to recharge. Other studies tackled this problem by considering other locations for energy storage systems (ESSs) and/or fast chargers throughout the network which can be used to charge the EBs without having to make a full trip back.

In [15], mixed-integer programming (MIP) was used to minimize the TOC of a real world transportation network of a town in the United States. The optimal deployment of fast charging stations and ESS throughout the network was achieved. Similarly, another study [16] utilized MIP to for optimal charging station planning for a transport network of a city in China. The objective in this case was to determine the optimal sizing and siting of the charging stations, which minimizes the total cost at each stage of the planning problem.

The most recent scientific literature addressing the problem of optimizing EB public transport networks have been surveyed, and compiled in Table 1. The conducted literature survey led to two main findings:

- All surveyed scientific publications have been concerned with the optimization of one or two elements of the transport system, with the other aspects being considered as model constraints.
- All studies were performed on specific case studies based on existing transport networks in real-world cities. No studies were found to model generic networks or testing the universal applicability of the proposed model.

Accordingly, the novel contributions and objectives of this work can be summarized as follows:

- A universal mathematical model for fully electric public transportation networks is developed and formulated as a mixed-integer linear programming (MILP) optimization problem with the objective of minimizing the TOC.
- The nature of the proposed model is universal, i.e., any set of routes, buses, and type of charging infrastructure can be considered as a parameter or a decision variable. In this sense, the model is highly versatile and can be used to optimize existing systems or to design new ones.

This manuscript is organized as follows: Section I introduced the background and motivation behind this work and highlighted the contributions. In Section II, the modeling of a public transport model is introduced by describing all the components of the system. In Section III, the mathematical formulation of the MILP optimization model is presented. In Section IV, three different case studies are performed in order to validate and demonstrate the proposed model. In Section V, a discussion of the applicability of the proposed model is presented, in addition to suggestions for future work aiming at extending or enhancing this model. Finally, in Section VI the conclusions of this study are summarized.

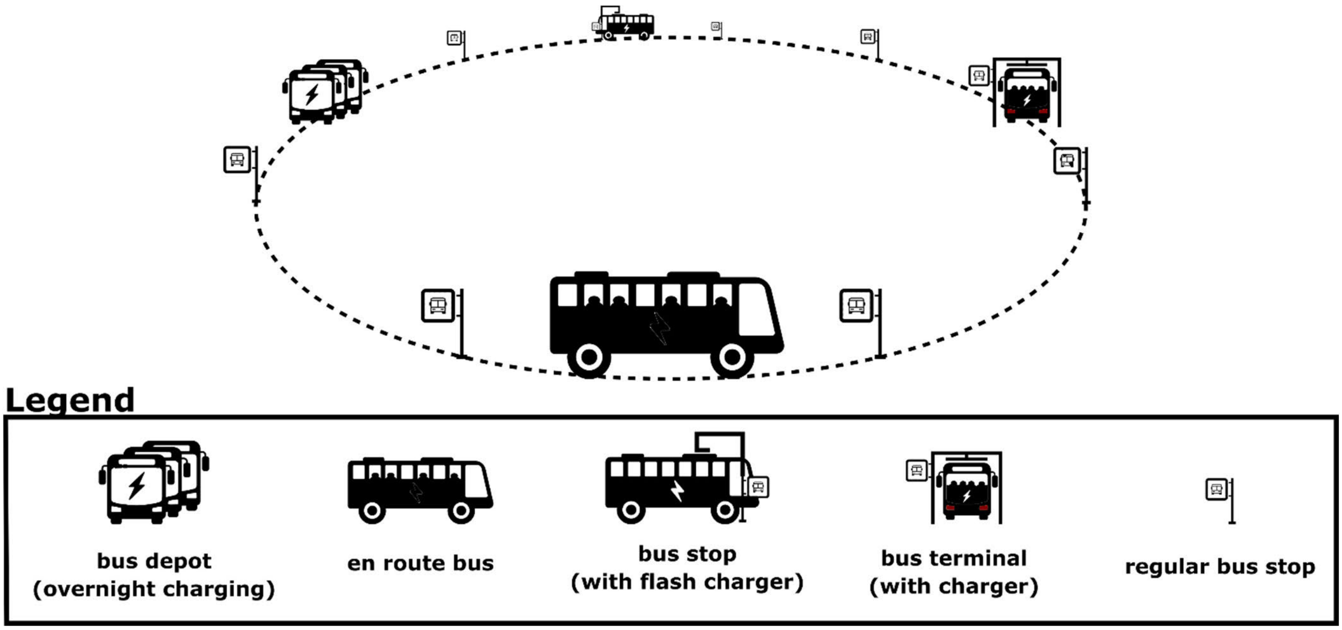

FIGURE 1. Illustration of a generic public transport network and its components: depots, buses, routes, stops, terminals, and charging infrastructure.

II. PUBLIC TRANSPORT NETWORK MODEL

In Fig. 1, a public transport system is illustrated along with its components. A generic system is comprised of the following components:

- *Depot:* The depot is where the buses are dispatched from, and is where they park and charge while they are not in service.
- *Electric Bus:* The electric buses (EBs) are the backbone of the network, traversing the routes with passengers on board. EBs have onboard batteries which are recharged at designated charging locations in the network.
- *Routes*: The routes are the paths which EBs must traverse to transport passengers. Routes are made up of bus stops and are scheduled. The scheduling can be based on a specific time at which the EB must arrive/depart from/to each spot, or a frequency for the EBs to traverse the route (e.g. 1 bus to pass by a stop every X minutes).
- *Terminals*: Terminals are usually bus stops at which several routes intersect and therefore have an allocated area and infrastructure for use by the EBs.
- *Charging Infrastructure*: The charging infrastructure provides the energy needs of the system. The chargers where buses can recharge their batteries can be off-route (e.g. at depots) or on-route (e.g. at terminals).

As illustrated in Fig 1, three main types of chargers are currently available commercially [17]–[19]. The first is the depot charger (DC), typically used to charge the buses during the time when they are out of service and parked at the depot (off-route). DCs typically have rated powers ranging from 50 kW to 100 kW, intended for slow charging of the batteries overnight or while they are out of service.

The second type of chargers is the terminal charger (TC). As the name suggests, a TC is typically installed for on-route charging at main terminals, with its rated power ranging from 500 kW to 600 kW. The TC charges the onboard battery through a converter, typically connected to the medium voltage (MV) power grid through a substation transformer at the terminal, as illustrated in Fig 2.

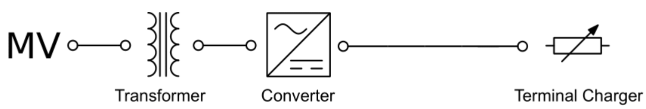

FIGURE 2. Schematic of a TC grid connection.

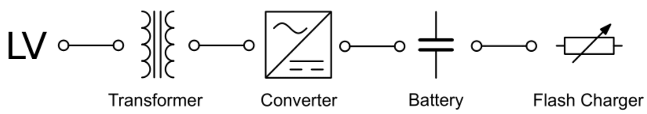

FIGURE 3. Schematic of a FC grid connection.

The third type is the flash charger (FC), used for on-route fast charging at regular stops, typically has a rated power ranging from 400 kW to 500 kW. Unlike the TC, the FC is installed at regular stops, and thus is connected to the low voltage (LV) power grid, typically coupled with a battery to avoid causing a load spike on the LV grid, which would be more sensitive to such load fluctuations as opposed to the MV ones. Another reason that buses spend more time stopped at terminals (a few minutes) compared to regular stops (a few seconds).

In fact, this is the main technical difference between TCs and FCs. Although their costs and rated powers are similar, the main different influencing the choice between the maximum time at which EBs can spend charging at either.

From a cost perspective, on-route chargers are typically associated with much higher (an order of magnitude) capital costs than depot chargers. The investment is justified by their fast charging rates, which allow EBs to charge on-route, decreasing the parking time at the depot, and thereby minimizing the number of idle buses in the network and total investment in batteries. This is one of the trade-offs which upholds the need for an optimization model for designing the charging infrastructure.

Accordingly, all three types of commercially available charging infrastructures (DC, TC, and FC chargers) and their aforementioned technical and economic characteristics are to be considered in the current model.

Most commercially available EBs are fitted with batteries with capacities ranging from 80 kWh to 320kWh [20], [21]. As such, in the current model the battery capacity of EBs assigned to each route are modeled as a design variable for the optimization problem.

Defining generic routes is crucial to establish an adequate framework for the optimization model. Routes can be categorized based on two key parameters [10], [22]:

- *Average Distance Between Stops:* This parameter is an indicator of the route location. Routes within large cities or densely populated areas are associated with shorter average distances between stops compared to those in suburban areas. This is expressed as:

$$d_r^s = \frac{L_r}{N_r^s - 1} \tag{1}$$

where d_r^s is the average distance between stops for route r. L_r is the length of route r, and N_r^s is the number of stops in route r.

- *Average Daily Distance:* Considering normal operation in which an EB is assigned a specific route each day, this is expressed as:

$$d_r^d = \frac{H_r}{T_r} \cdot L_r = N_r^t \cdot L_r \tag{2}$$

where d_r^d is the average daily distance on route r. H_r is circulating hours of route r (difference between first and last bus of the day), T_r is the average duration of the route, and N_r^t is the daily number of trips in route r.

Having defined these two key parameters, generic routes can be categorized into different types to provide physical meaning. In this study, the categorization defined in Table 2 is used to describe different routes in the case studies. Accordingly, generic routes can be categorized into city (CC) or suburban (SU) routes based on d_r^s, or as short (SD), medium (MD), or long distance (LD) based on d_r^d.

III. OPTIMIZATION MODEL

As any optimization problem, the proposed MILP model consists of two main elements: the objective function and problem constraints, which are detailed subsequently.

A. OBJECTIVE FUNCTION

Note that in the current formulation the TOC is calculated as an annual value. Electricity charging costs are operating costs and therefore the annual value can be calculated directly. However, the charging infrastructure and battery costs have capital investments, and therefore the capital cost is divided by the equipment lifetime and summed to the yearly operating costs to obtain their equivalent annual cost:

$$annual\ cost = \frac{capital\ cost}{life\ time} + annual\ operating\ cost \tag{3}$$

The objective function to be minimized represents the TOC of the transport system and is shown in (4). For each route in the system, the annual TOC is calculated as the summation of five cost terms. The five cost terms, from left to right, correspond to: the annual running cost of the depot station(s), annual ownership costs of batteries for all buses in circulation, annual ownership cost of all the entire charging infrastructure, annual electricity cost for on-route charging (by TCs and FCs), and finally the annual electricity cost for off-route charging (by DCs). Each of the five terms is elaborated in (4)-(9).

$$\textbf{min TOC} = \sum_{r \in R} \left(\boldsymbol{C_r^{depot}} + \boldsymbol{C_r^{batteries}} + \boldsymbol{C_r^{chargers}} + \boldsymbol{C_r^{onroute}} + \boldsymbol{C_r^{offroute}} \right) \tag{4}$$

$$C_r^{depot} = d_r \cdot C^d \tag{5}$$

$$C_r^{batteries} = \sum_{k \in B^r} \left(b_{k,r} \cdot C^B \right) \tag{6}$$

$$C_r^{chargers} = \sum_{i \in I^r} \sum_{h \in H} x_{i,h,r} \cdot C_h^C \tag{7}$$

$$C_r^{onroute} = \sum_{i \in I^r} \sum_{j \in J^r} \left(e_{i,j,r} \cdot C_{i,j,r}^E \right) \cdot d_{year} \cdot n_r^{bus} \tag{8}$$

$$C_r^{offroute} = e_{end,r} \cdot C_{end,end,r}^E \cdot d_{year} \cdot n_r^{bus} \tag{9}$$

The first term (C_r^{depot}) corresponds to the depot charger annual TOC for each route r and is expressed in (5). The term is a multiplication of a binary variable (d_r) representing the existence of the depot charger (for route r) multiplied by the annual ownership cost of running a depot charger (C^d).

The second term, $C_r^{batteries}$, is the annual TOC of all batteries in route r and is shown in (6). For each route, this is the

TABLE 2. Categorization of generic routes into City (CC), Suburban (SU), Short (SD), Medium (MD), and Long (LD).

		d_r^d (km)		
		<200	200-250	>250
d_r^s (km)	<0.3	CC-SD	CC-MD	CC-LD
	>0.3	SU-SD	SU-MD	SU-LD

summation of the battery costs of each bus k deployed to this route (B^r is the set of all buses deployed to route r) which is calculated as the capacity of each battery ($b_{k,r}$) multiplied by its annual ownership cost (C^B) per-kWh.

The third term ($C_r^{chargers}$) is shown in (7) and corresponds to the annual cost of the charging infrastructure on each route r. Here, i and h are the positive integer indices for the stops and charger type, respectively, and I^r and H are the set of all stops in route r and set of available on-route charger types, respectively. For each route r, $x_{i,h,r}$ is a binary variable indicating the presence of a charger of type h at stop i, and C_h^C is the annual ownership cost of a charger of type h. Accordingly, $C_r^{chargers}$ is calculated for each route r as the sum of the annual cost of all present charger types (decided by the binary variable) at each stop, and is summed for all stops.

The fourth and fifth terms in (8) and (9) correspond to the total cost of energy supplied to recharge the batteries through on-route and off-route chargers, respectively.

In Eq. (8), j corresponds to the index of the trip in J^r, which is the set of all daily trips made on route r (the number of daily trips made on each route is determined by the frequency of the route). For each route r, $e_{i,j,r}$ and $C_{i,j,r}^E$ are the energy charged at stop i during trip j, and the corresponding cost per unit of electricity, respectively. d_{year} is the number of days in a year, set as 365, and n_r^{bus} is the total number of buses traversing the route. This last value can be calculated based on the two parameters of each route which were introduced in (1) and (2), as is shown in (10):

$$n_r^{bus} = \frac{H_r}{N_r^t} \cdot F_r^b \tag{10}$$

In (10), F_r^b is the frequency of buses is route r and the other variables have been defined in Section II.A.2. Accordingly, $C_r^{onroute}$ is calculated for each route r as the sum of the annual cost of electricity charged at all stops, for all trips.

In Eq. (9), the final term of the TOC objective function is shown ($C_r^{offroute}$) which is the cost of electricity charged off-route (while the EBs parked or are not in service) for route r. In this equation, $e_{end,r}$ and $C_{end,end,r}^E$ and correspond to the energy charged at the end of the route (i.e., off-route), and the corresponding cost per unit of electricity, respectively. It is important to note that in this formulation, the last stop in a bus schedule corresponds to the depot. However, this does not dictate the presence of a charger at the depot (DC), which is a decision variable dependent on the binary variable d_r. With all the terms being defined, the objective function for the transport system TOC is evaluated as the summation of the total costs of all routes in the network, denoted by set R.

B. CONSTRAINTS

The constraints of the optimization problem can be divided into four groups:

1) INFRASTRUCTURE CONSTRAINTS

The first constraint is associated with the charging infrastructure, and guarantees that at each stop there is only one type of charger installed (based on the binary decision variable $x_{i,h,r}$ which was previously introduced), as is represented in (11).

$$\sum_{h \in H} x_{i,h,r} \le 1, \quad \forall r \in R,\ \forall i \in I^r \tag{11}$$

2) BATTERY CONSTRAINTS

The second set of constraints are associated with the batteries onboard the EBs, and are represented by (12)-(14). To protect the health of the batteries, for each bus k, the battery State-of-Charge (SoC), denoted by $E_{i,j,k,r}$, must be within the upper and lower bounds $\bar{B}$ and $\underline{B}$, as set by (12) and (13), respectively. As defined in the previous section, $b_{k,r}$ is the capacity of the battery installed on bus k deployed to route r. In (14), sets the SoC boundary conditions to be at the maximum value ($\bar{B} \cdot b_{k,r}$) I.e., the EB starts each trip from the depot with full charge. It is important to note that with the circular bus route nature, the first and last stops are the same. I.e., stop $i = 1$ is the same as $i = end$. Hence, the SoC at both, $E_{1,j,k,r}$ and $E_{end,j,k,r}$, are equal as set by (14). Constraints (12)-(14) are applied globally: at each stop in each route for all buses deployed to all routes.

$$E_{i,j,k,r} \le \bar{B} \cdot b_{k,r}, \quad \forall r \in R,\ \forall i \in I^r,\ \forall j \in J^r,\ \forall k \in K^r \tag{12}$$

$$E_{i,j,k,r} \ge \underline{B} \cdot b_{k,r}, \quad \forall r \in R,\ \forall i \in I^r,\ \forall j \in J^r,\ \forall k \in K^r \tag{13}$$

$$E_{1,j,k,r} = E_{end,j,k,r} = \bar{B} \cdot b_{k,r}, \quad \forall r \in R, \quad \forall i \in I^r,\ \forall j \in J^r,\ \forall k \in K^r \tag{14}$$

3) CHARGED ENERGY CONSTRAINTS

The third set of constraints in (15)-(21) are related to the energy exchange between the EBs and the charging infrastructure. First, (15) ensures that energy can only be injected from the electrical grid to the EBs through the chargers and not vice-versa. This constraint can easily be modified or removed in case bi-directional energy flow with the power grid is possible and to be considered. Constraint (16) dictates that if there is no charger installed at a stop ($x_{i,h,r} = 0$), then the energy exchanged at that stop must be equal to zero ($e_{i,j,r} = 0$). Constraint (17) sets the charging power according to the charger type installed at a stop ($x_{i,1}$, $x_{i,2}$, etc.), matching it to the corresponding maximum charging capacity of this charger type ($\overline{E}_1$, $\overline{E}_2$, etc.).

Constraints (18) and (19) imposes $x_{i,h,r}$ that there can only be one type of charger at each stop in each route. In case there is a depot charger ($d_r = 1$), constrain (20) limits charging at the end of each trip to correspond to the maximum charging capacity of the depot charger ($\overline{E}_{DC}$). Constraint (21) imposes that there must be a charger installed at the first/last stop of each route, such that if there is no depot charger ($d_r = 0$), charger type 1 (e.g. terminal charger) is imposed on that stop to comply with constraint (14). In this sense, the model optimizes the design of the system by choosing between the depot charger and the cheapest opportunity charger depending on which is more cost effective. In real-life terms, this is seen in the case that some routes start/end at terminal (with a TC) and other start and end at the main depot (with a DC).

$$e_{i,j,r} \geq 0, \quad \forall r \in R,\ \forall i \in I^r,\ \forall j \in J^r \tag{15}$$

$$\sum_{h \in H} x_{i,h,r} = 0 \Longrightarrow e_{i,j,r} = 0, \quad \forall r \in R,\ \forall i \in I^r,\ \forall j \in J^r \tag{16}$$

$$x_{i,h,r} = 1 \Longrightarrow e_{i,j,r} \leq \overline{E}_h, \quad \forall r \in R,\ \forall i \in I^r,\ \forall j \in J^r \tag{17}$$

$$\sum_{h \in H} x_{i,h,r} \geq 0, \quad \forall r \in R,\ \forall i \in I^r \tag{18}$$

$$\sum_{h \in H} x_{i,h,r} \leq 1, \quad \forall r \in R,\ \forall i \in I^r \tag{19}$$

$$d_r = 1 \Longrightarrow e_{end,j,r} \leq \overline{E}_{DC}, \quad \forall r \in R,\ \forall j \in J^r \tag{20}$$

$$d_r = 0 \Longrightarrow, x_{end,1,r} = 1, \quad \forall r \in R \tag{21}$$

4) ENERGY BALANCE CONSTRAINTS

The final constraint in (22) is associated with the total energy balance of the system, such that the total SoC consumed by all buses is equal to the total SoC charged.

The equation is applied for all buses deployed to all routes in the network, such that for each bus, the sum of the SoC difference between all subsequent stops ($E_{i,j,k,r} - E_{i-1,j,k,r}$), must be equal to the total energy charged at all stops (including the terminal or depot).

$$\sum_{i=2\ldots end} \left(E_{i,j,k,r} - E_{i-1,j,k,r} + e_{i,j,k,r}\right) = 0 \qquad \forall r \in R, \quad \forall j \in J^r,\ \forall k \in K^r \tag{22}$$

C. COMPUTATIONAL IMPLEMENTATION

The YALMIP package (version R20181012) was used as the algebraic modeling language (AML) for the proposed model, on MATLAB (version R2019b). The Gurobi solver (version 8.0) was used to optimize the system using MILP.

Here it is important to note that the model of the system and the optimization algorithm employed are distinct. The main objective of this work is to formulate a generalized mathematical formulation which allows the modeling of all components of any generic fully electric public transport network. Given that the design problem is offline in nature, the choice of deterministic optimization is generally favored over a meta-heuristic one, which would yield sub-optimal solutions. The choice of a MILP optimization solver was due to its deterministic nature which guarantees the global optimal value for any given case using the proposed formulation.

IV. CASE STUDIES

A. DESCRIPTION OF THE DIFFERENT CASE STUDIES

In order to validate and demonstrate the universal applicability of the proposed optimization model on a wide range of problems, three case studies were performed:

1. In the first case study, three generic routes are constructed with different lengths. The proposed model is used to determine the optimal design, sizing, and siting of the charging infrastructure in addition to the sizing of the batteries for each of the given routes.
2. In the second case study, a generic transportation network is constructed based on a combination of 180 different routes, belonging to all six categories (CC-SD, CC-MD, CC-LD, SU-SD, SU-MD, and SU-LD). The optimal design, sizing, and siting of the charging infrastructure in addition to the sizing of the batteries for all deployed EBs and routes in the entire system is determined.
3. In the third case study, a long-term transport network planning problem is investigated, by studying the effect of long-term (10-year ahead) forecasted change on battery costs on the results obtained in the second case study. A comparative analysis is then performed between the present-day (2020) and future (2030) scenarios in terms of the TOC of the network and its respective breakdown.

The three defined case studies allow the validation of the proposed model in terms of its applicability on different classes of transport system design problems, namely the optimization of specific routes, design of large-scale system, and long-term optimal investment planning of large-scale transport systems.

TABLE 3. Specifications of routes used for the first case study.

	Route A	Route B	Route C
Number of Trips (per day)	5	15	15
Number of Stops (per trip)	75	60	80
Total Number of Stops (per day)	375	900	1200
Trip Length (km)	20	15	20
Bus Size (m)	18	18	24
Average Consumption (kWh/km)	1.8	1.8	2.2

TABLE 4. Classification of commerically available EBs according to average energy consumption [2], [7], [8].

Bus Type	Average Consumption (kWh/km)
12-meter	1.2
18-meter or articulated	1.8
24-meter or double articulated	2.2

TABLE 5. Techno-economic specifications of chargers.

	DC	TC		FC	
Charger Classification	Depot	On-Route		On-Route	
Model	Standard	Slow	Fast	Slow	Fast
Rated Power (kW)	50	400	600	400	600
Maximum Charging Time	5 hours	3 minutes		10 seconds	
Capital Cost (EUR)	98k	278k	280k	278k	2780k
Operating Cost (EUR/year)	100	2k		2k	
Lifetime (years)	20	20		20	

TABLE 6. Techno-economic specifications of batteries.

Capital Cost (EUR/kWh)	250
Operating Cost (EUR/year)	-
Battery Lifetime (years)	5
State-of-Charge Upper Boundary (%)	90
State-of-Charge Lower Boundary (%)	10

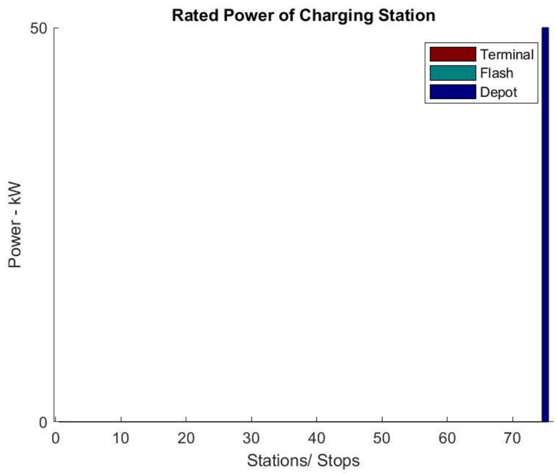

FIGURE 4. Charger deployment for Route A.

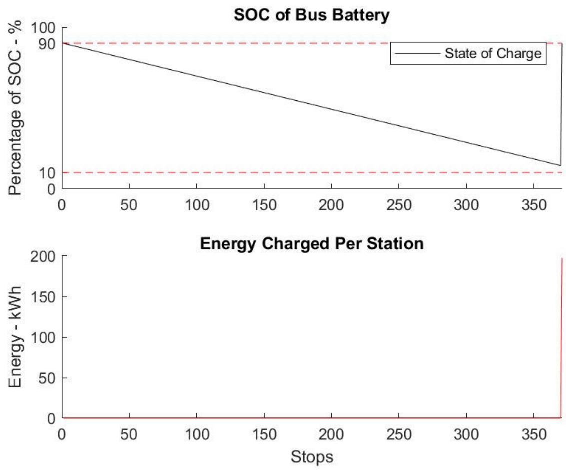

FIGURE 5. Battery SoC variation (top) and energy charged at each station (bottom) during the full daily cycle of Route A.

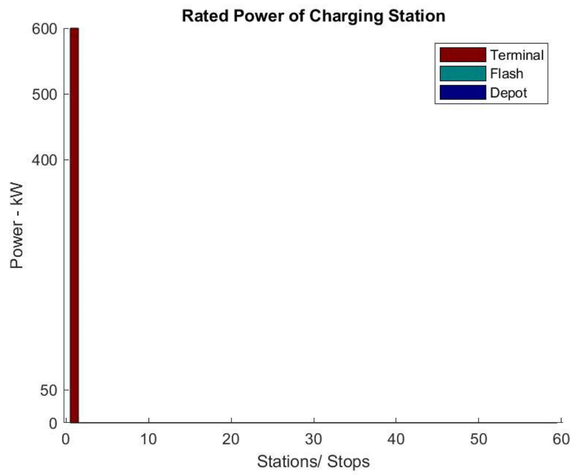

FIGURE 6. Charger deployment for Route B.

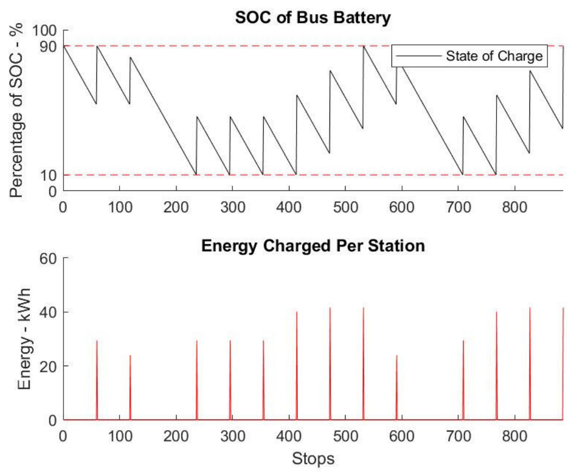

FIGURE 7. Battery SoC variation (top) and energy charged at each station (bottom) during the full daily cycle of Route B.

B. CASE STUDY DEFINITIONS AND RESULTS

1) OPTIMAL DESIGN OF INDIVIDUAL BUS ROUTES (CASE STUDY 1)

In this first case study, the objective is to test and validate the proposed mathematical formulation, by attempting to determine the optimal charging infrastructure deployment and battery sizing for individual EB routes. For this purpose, three generic routes are constructed with different lengths, as detailed in Table 3. Based on length of the route, different bus sizes are needed for each route, whose specifications are in accordance with Table 4. Techno-economic specifications of commercially available chargers to choose from and the batteries are provided in Tables 5 and 6, respectively (based on information by ABB Canada and Siemens [18], [19]). The latter are constrained between 80 kWh and 320 kWh with 20 kWh increments. In the first case study, n_r^{bus} is set to unity for all routes, i.e. one EB dispatched to each route.

The result for the optimal charger deployment in Route A is shown in Fig. 4. As can be seen, only the depot charger with a 50 kW power rating is sufficient to sustain the energy demand of the EB throughout its 5 cycles of the route per day. The result of the optimal battery capacity was 260 kWh. In Fig. 5, one can see that a full charge at the depot can sustain the full daily cycle of the route by the EB before reaching the minimum bound of 10% SoC.

With Route B being significantly longer (threefold the distance of Route A), investment in a higher charging power is necessary. In Fig. 6, the optimal deployment is shown to be that of one 600 kW TC to sustain the route. With this, only a 80 kWh battery is needed. As such, the optimal solution as here as opposed to Route A consisted of investing in a more powerful charger while saving the costs by using smaller batteries on the deployed EB The optimal charging schedule is shown in Fig. 7, where it can be seen that the EB occasionally stops at charges at the TC to recharge its battery throughout the day, guaranteeing a full SoC at the end of the route for its next deployment.

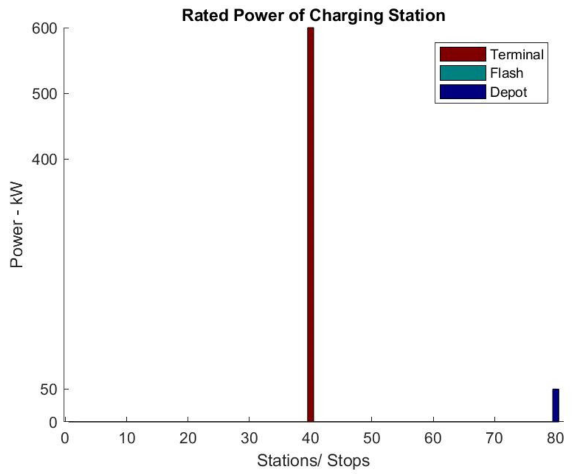

FIGURE 8. Charger deployment for Route C.

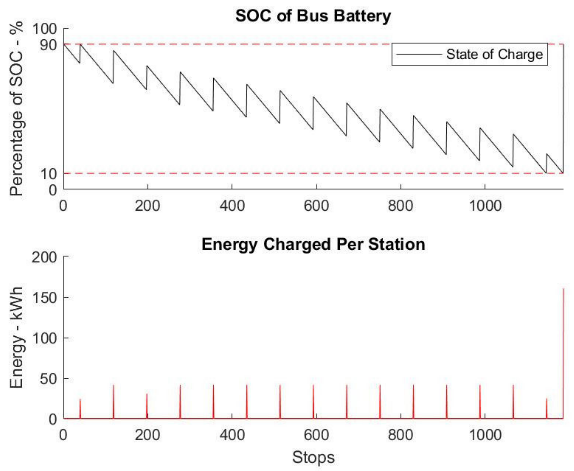

FIGURE 9. Battery SoC variation (top) and energy charged at each station (bottom) during the full daily cycle of Route C.

For Route C (the longest of the three), the optimal charger configuration consisted of both a 600 kW TC and a 50 kW DC (as shown in Fig. 8), with a medium-sized 200 kWh battery capacity for deployed EBs. The SoC variation throughout the day (Fig. 9) shows that the EB stops to recharge its battery every cycle of the route, gradually decreasing the SoC at the end of every cycle. Finally, at the end of the day, the EB is recharged at the depot to a full SoC for its next deployment.

The optimal annual TOC (objective function of the model) and its breakdown for each route are detailed in Table 7 and illustrated in Fig. 10 and detailed in Table 6.

One can observe that for the shortest Route (A), the lowest TOC is encountered and investment in high capacity batteries on board the deployed EB is sufficient to support the route requirements. In this case, investment in high power and/or fast chargers is not cost-effective, with the DC sufficing.

As the length of the route increases as in Route B, one can see that a the optimal design involves investing more in

TABLE 7. Resulting optimal design and total ownership cost breakdown for each of the first case study routes.

	Route A	Route B	Route C
Optimal Battery Size (kWh)	260	80	200
Number of DC (50 kW)	1	0	1
Number of TC (500 kW)	0	0	0
Number of TC (600 kW)	0	1	1
Number of FC (400 kW)	0	0	0
Number of FC (500 kW)	0	0	0
Cost of Chargers (EUR/year)	5000	16000	21000
Cost of Batteries (EUR/year)	13000	4000	10000
Cost of Electricity (EUR/year)	3918	11181	18614
Annual TOC (EUR/year)	21918	31181	49614

the charging infrastructure, and the tradeoff between battery capacity and charging power becomes cost-effective. However, as the route length is further increased in Route C, a more complex design is needed in terms of charger types and battery sizing. It is noteworthy that for these three routes, (all being CC-type routes), the installation of a FC is not found to be cost-effective.

2) OPTIMAL DESIGN OF ELECTRIC BUS TRANSPORT SYSTEM (CASE STUDY 2)

In the second case study, the proposed optimization model is tested and validated for the design of a full electric bus transport system. While the objective is to test the applicability of the proposed model for any generic transport network, it is important to also maintain the true-to-life nature of the case study.

Therefore, two major cities with high EB presence who also publicly provide their full bus route information have been analyzed: Paris, France [23] and London, UK [24]. The routes were categorized based on the categories proposed in Table 2, and the corresponding statistics are presented in Fig. 11. Due to the large metropolitan nature of both transport networks, it was predictable that the routes would be almost equally divided between CC and SU types (44% and 56%, respectively). Also, as expected, the majority of city routes were short-distance (CC-SD), while the majority of suburban routes were long-distance (SU-LD), with the two types combined making up more than half of the total routes (53%).

Following this analysis, it is possible to generate a set of routes which represents a generic public transport system, while maintaining its realism by emulating the route category distribution of real-life public transport systems. Accordingly, a generic public transport network consisting of 180 routes was constructed. The routes were generated based on random pairs of d_r^s, and d_r^d values (defined in

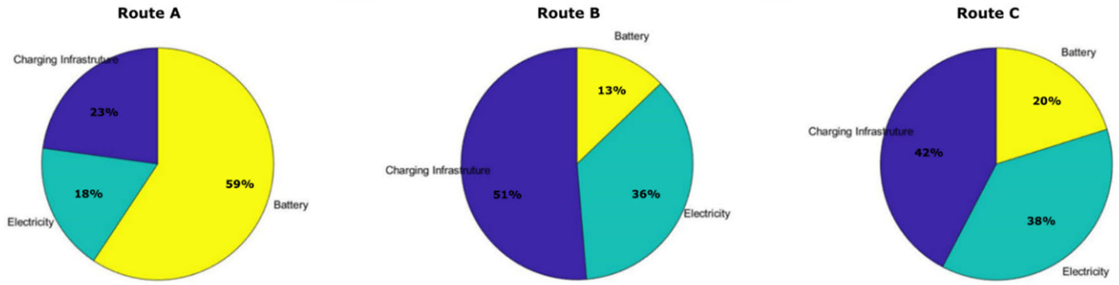

FIGURE 10. Breakdown of the optimal design TOC for the first case study routes: Route A TOC (left, total of 21918 EUR/year), Route B TOC (center, total of 31181 EUR/year), Route C TOC (right, total of 49614 EUR/year).

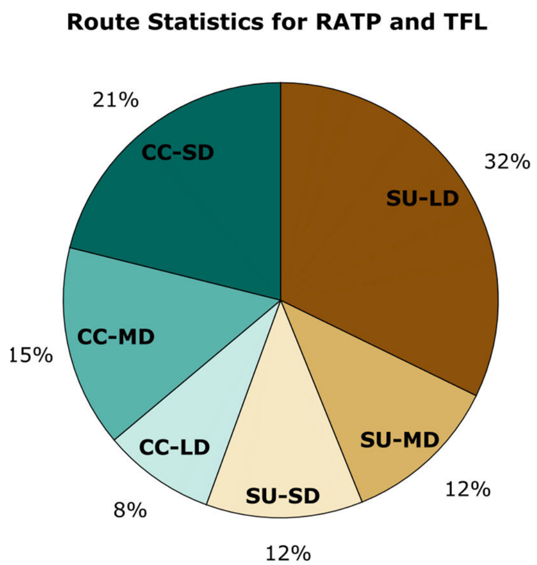

FIGURE 11. Breakdown of the different route categories based on the networks of RATP and TFL.

Section II and Table 2), while maintaining the share of the route categories as per the real world systems (as in Fig. 11). The key parameters (d_r^s, and d_r^d) for each of the 180 routes forming the generic public transport network are shown in Fig. 12.

With the routes defined, the proposed MILP model can be used to optimize the design of the charging infrastructure and battery sizing to achieve a minimum TOC of this generic transport network. The techno-economic specifications of the EBs, chargers, and batteries are used according to Table 4, Table 5, and Table 6, respectively. Average hourly electricity prices for the European energy market [25] are used (distributed based on respective scheduling of stops). In addition, due to the nature of urban environments with frequent breaking and stopping, an added penalty of 10% increased electricity consumption per kilometer driven is used for CC routes to estimate these effects in the generic network. The frequency for all the routes is set to a high frequency (HF) of 15 minutes, and the EB deployment is calculated according to (10).

The results for the optimal charger deployment and battery sizing for the entire network are shown in Fig. 13. For CC-SD and CC-MD routes, the charging infrastructure is seen to be mainly comprised of TCs along with low-capacity batteries, with a few exceptions where an additional DC and augmented battery capacity is needed, when the distance between stops is larger and the bus type has a higher consumption. Only one CC-LD route requires the use of a FC, and this can be attributed to the high power consumption of this route. For suburban routes, it is clear that there is an increased reliance on on-route charging with increased battery capacities. This is especially the case for longer-distance routes, when the use of FC becomes common, as the distance between stops and the total length of the routes become very large.

The results in Fig. 14 for the TOC breakdown shows that for all SD routes (CC or SU), the majority of the TOC corresponds to battery costs, followed by charging infrastructure and electricity costs. For MD and LD routes, the majority of the TOC becomes that of the charging infrastructure, followed by electricity (more prominent due to larger distances), and then batteries (less prominent due to more frequent on-route charging).

These patterns appear to be the same for both CC and SU routes. That is, despite the fact that suburban routes have a higher TOC than their city counterparts, the TOC breakdown (percentage share of batteries, charging infrastructure, and electricity consumption) is significantly more dependent on the length of the route (SD/MD/LD) rather than the distance between stops (CC/SU).

In order to analyze the effect of the route frequencies, the simulation is repeated for the same network, albeit with a low frequency (LF) 1 hour instead of 15 minutes (i.e., all routes reduced by a factor of 4 compared to the former HF case). The results are shown in Fig. 15.For the most part, the solution is very similar to the HF case, with a few differences noted. First, for SD routes, it can be observed that with a lower overall number of buses traversing the routes, it becomes more cost-effective to invest in DCs and larger battery capacities. Overall, HF routes have a higher number of TC due to their larger bus fleet, prioritizing cost reduction in batteries while LF ones with smaller bus fleets rely on bigger batteries with the additional DCs.

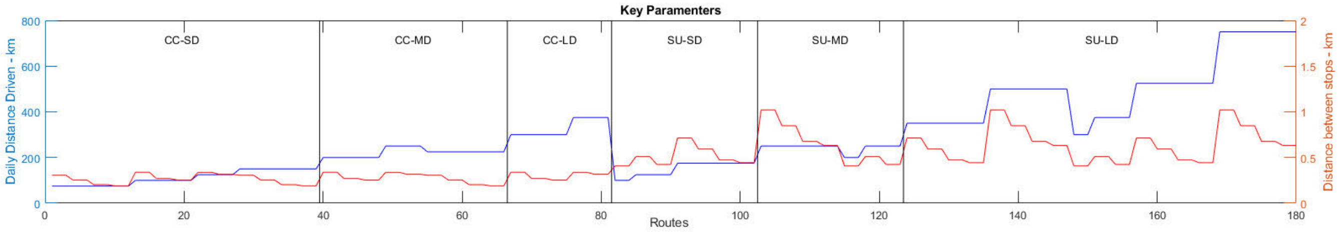

FIGURE 12. Key parameters (d_r^s, and d_r^d) for each of the 180 routes making up the generic public transport network for the second case study.

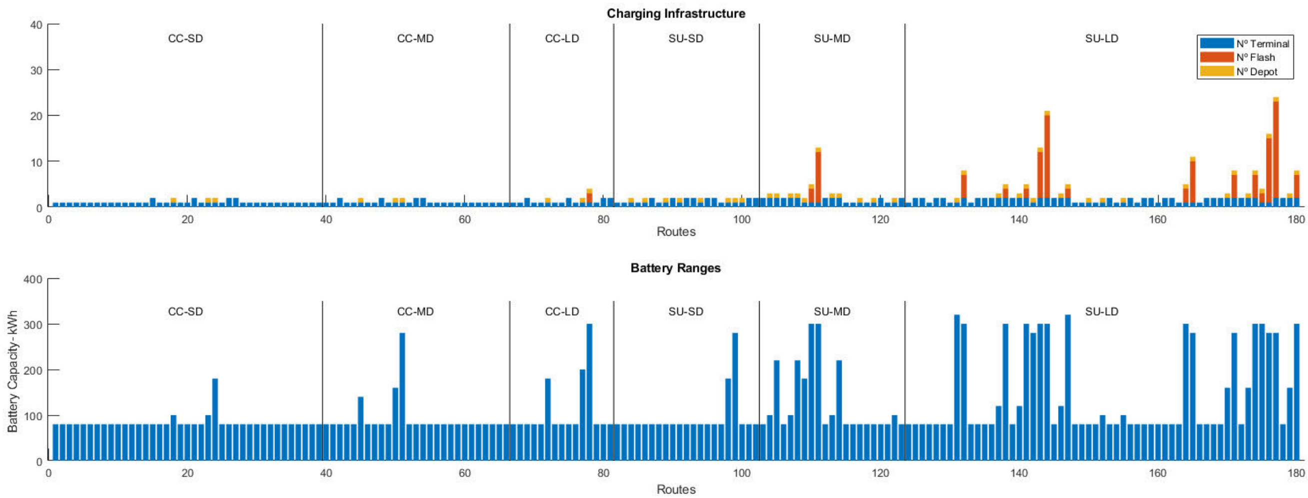

FIGURE 13. Results for the optimal charging infrastructure (top) and battery sizing (bottom) for all 180 routes of the generic public transport network under study, with a HF.

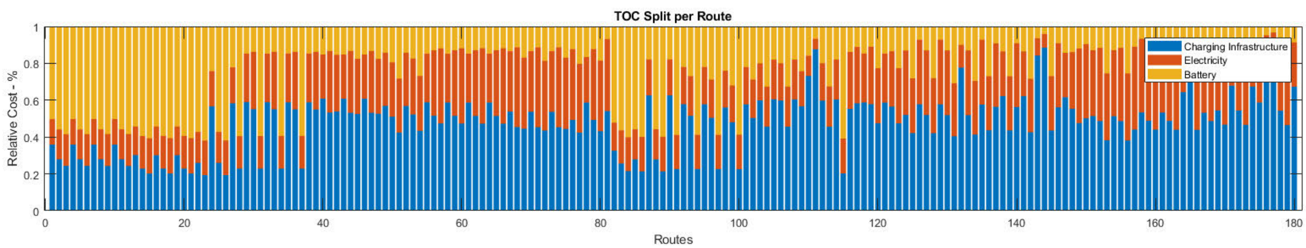

FIGURE 14. Breakdown of the resulting TOC for all 180 routes of the generic public transport network under study, with a HF.

3) LONG-TERM INVESTMENT PLANNING FOR AN ELECTRIC BUS TRANSPORT SYSTEM: 2030 SCENARIO (CASE STUDY 3)

The final case study used to validate the proposed model is based on a long-term planning problem, in which investment options are analyzed considering the forecasted change in the cost of acquiring and operating technologies.

By considering the predictions made in the report by Bloomberg [26], the constructed network in the previous case study is modified for a 2030 scenario (10 years ahead) by making the following modifications:

- Battery cost reduced to 62 EUR/kWh.
- Upper range of battery capacities increased to 400 kWh.
- Decrease in flash charger cost by 40% for stops close in proximity (due to increased ease of sharing one transformer and converter for FCs closer to each other).
- Decrease in terminal charger cost by 10% due to technological advancements.
- Remove the electricity consumption penalty for CC routes (due to the foreseen advance in regenerative breaking technologies).

For this updated 2030 scenario, the model is re-run for both the HF and LF cases, and the results are shown in Fig. 16 and Fig. 17, respectively. Three main changes are observed:

First, there is a clear increase in DC deployment, with larger battery capacities in CC-SD and SU-SD routes, regardless of the bus frequency. This effect is to be expected as the estimated decrease in battery cost overcomes the advantages of TCs.

Secondly, despite their (future) costs being sharply reduced in this scenario, FCs appear even less often than they did

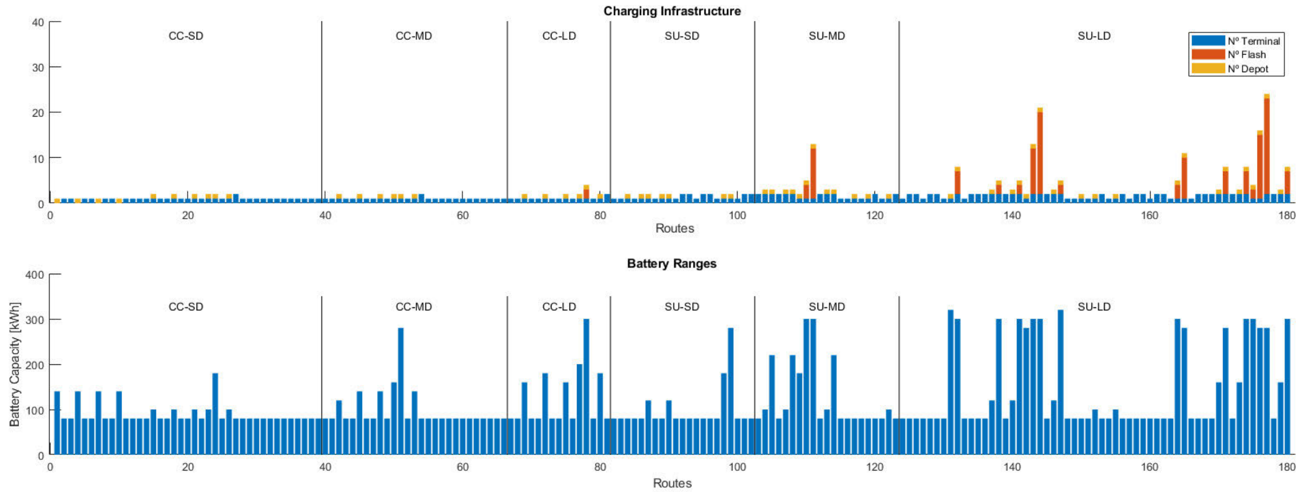

FIGURE 15. Results for the optimal charging infrastructure (top) and battery sizing (bottom) for all 180 routes of the generic public transport network under study, with a LF (reduced by a factor of 4 compared to the HF case).

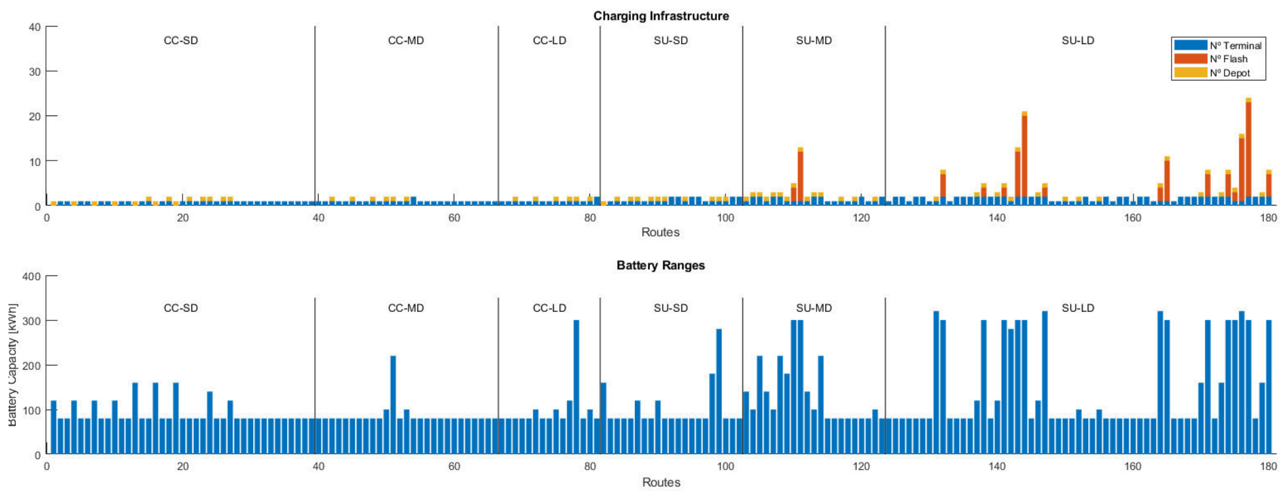

FIGURE 16. Results for the optimal charging infrastructure (top) and battery sizing (bottom) for all 180 routes of the generic public transport network under study, with a HF, repeated for the 2030 scenario.

(being deployed rarely and only for SU-MD and SU-LD due to high power consumption requirements).

Third, for LF routes there is a significant increased reliance on larger battery capacities and less on fast charging infrastructure, with batteries taking up a larger percentage share of the route TOCs as opposed to the 2020/present-day scenario. This may suggest that according to the assumptions used for the 2030 scenario, benefits from cost reductions in battery technologies will outweigh those in fast charging technologies.

In Fig. 18, the percentage decrease in the TOC (relative to the 2020/present-day scenario) is shown for all the routes and for the HF and LF cases. It is clear that there is a considerable decrease ($>30\%$) in the TOC of SD routes, and a smaller decrease ($>10\%$) for LD ones. This is due to the same reasons expressed above, with SD being shown to be more dependent on larger battery capacities and thereby achieving more saving with advanced and cheaper technologies thereof. HF routes can be seen to expect higher cost reductions, although this can be attributed to the fact that a larger fleet translates to higher contribution from batteries, leading to a greater impact of the aforementioned points, increasing the overall cost reduction.

Overall, from this analysis one can see that the current trend and policies in electrification of public transport systems are well justified for long-term prospects.

It is important to note that this case study is merely used here to showcase the applicability of the proposed model in analyzing future scenarios. The assumptions made for the 2030 scenario were for demonstration purposes, and an exact analysis of forecasted techno-economic values is a very complex problem and indeed out of the scope of the current work. With this being said, the applicability of the proposed model to analyze different forecasts for future scenarios has been

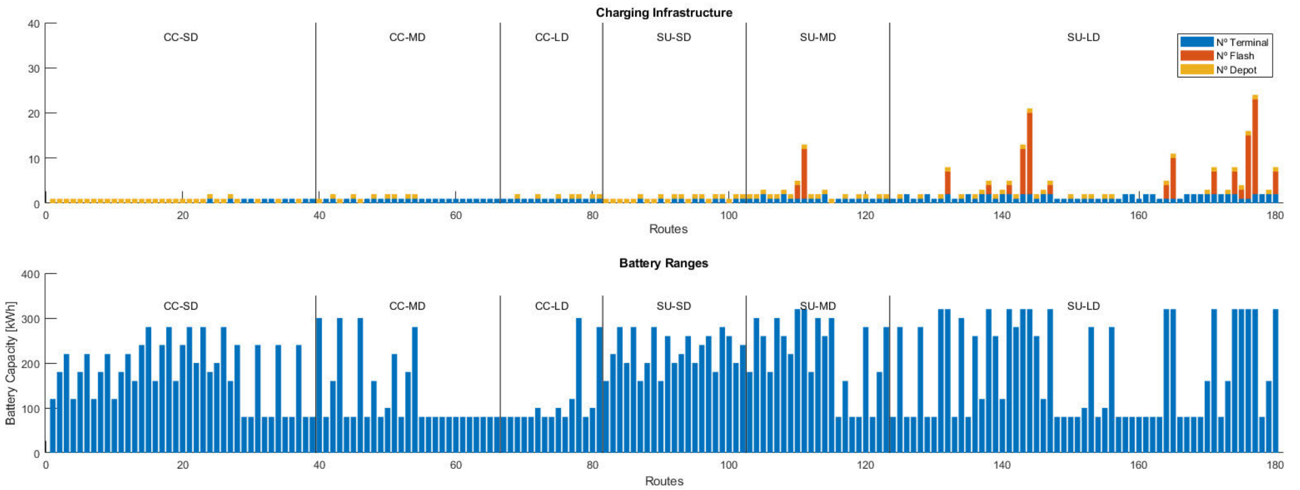

FIGURE 17. Results for the optimal charging infrastructure (top) and battery sizing (bottom) for all 180 routes of the generic public transport network under study, with a HF, repeated for the 2030 scenario.

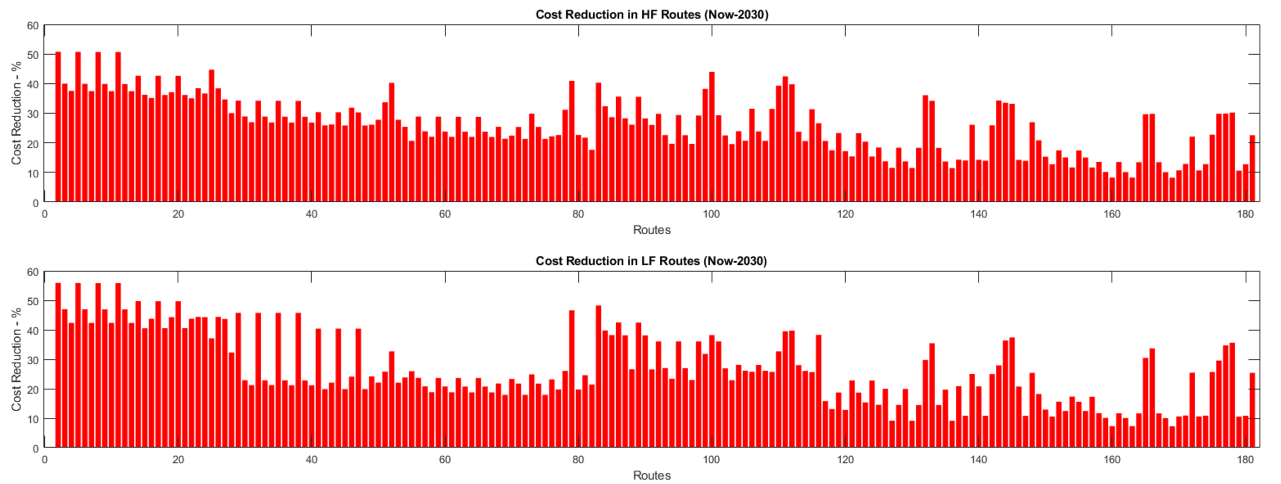

FIGURE 18. Route TOC decrease in the 2030 scenario (relative to the 2020/present-day scenario), shown for the HF (top) and LF (bottom) cases.

validated, and is indeed recommended for future research building up on this work, which is discussed in more detail in the next section.

V. DISCUSSION AND RECOMMENDATIONS FOR FUTURE WORK

The proposed MILP optimization model's applicability on any generic EB route or public transport system was demonstrated. In the first case study the model was shown to determine the optimal charging infrastructure deployment, battery sizing, and charging schedule for individual routes. In the second case study, the proposed model was shown to determine the optimal design on the level of a full system, determining the optimal charging infrastructure deployment, battery sizing, and charging schedule for all routes which guarantee the minimal TOC. Finally, in the third case study, it was shown that the proposed model can be used to analyze different future scenarios for long-term planning of planning of public transport systems.

As such, the proposed model was shown to be versatile in the sense that it can be used for a wide spectrum of problems and applied on any generic transport network. This also presents a lot of opportunities for future research building up on this work. Several recommendations can be made for future and follow-up studies by discussing the findings of this work:

- The case studies were purposefully chosen as generic cases in order to emphasize that the proposed model is not case-specific and not specifically fitted to any existing network structure or problem. While this is useful to showcase the versatility and universal nature of the proposed mathematical model, one limitation of the use of generic case studies is the lack of a benchmark to compare the optimal solution against. I.e., if no optimization model is employed, then in this case the system would be an "arbitrarily" or "heuristically" designed one (in literature this is sometimes referred to as an "experience-based" approach [11]), and in the case of a generic system there would be an infinitely large number of sub-optimal possible designs to consider. With MILP optimization employed, being a deterministic method in nature, the global optimal solution is guaranteed, so this does not retract any of the conclusions made from the performed case studies. However, since most real-life systems are designed using said "experience-based" approaches [11], it would be insightful to model full-scale real-life public transport networks and highlight the potential benefit of applying the proposed to improve their design. Moreover, using the proposed model to optimize real-life transport networks from different countries/regions may provide valuable insight on regional differences to consider and evaluate design considerations in different regions.

- Although hourly varying electricity prices corresponding to modern SGs and their demand-side management strategies were considered in this model and the case studies, more complex grid interaction can be modeled between EB networks and the power grid. Previous studies such as [13] have evaluated such "grid-interactive" bus operation problem for existing networks. The benefits of grid-interaction can be leveraged if considered early-on in the design phase, and can increase profitability since ancillary services provided to the grid can bring about considerable profit for the network owner [3]. No studies were found to consider this aspect. As such, its incorporation into the optimization model is recommended for future studies building up on this work.
- Accounting for resource sharing can be an interesting and valuable point to consider. For instance, sharing the charging infrastructure with other transport networks (belonging to different owners/companies), or other facilities such as EV parking lots [27] can be mutually beneficial to both parties and help decrease overall TOC, and thereby recommended to be analyzed in future work. Moreover, battery-swapping strategies for EVs were shown to improve the techno-economic operation of consumer-owned EVs, as shown in [28], and therefore a potentially viable strategy to be used to further improve EB systems.
- In the third case study, a 2030 scenario was analyzed based on several assumptions for future technology advancements. A similar sensitivity analysis is recommended to be performed for present-day scenarios, albeit in different countries or regions. Globally, costs of acquiring and operating different technologies, in addition to implemented socio-economic policies significantly vary between different regions. This is recommended as a future analysis as it can provide insight on different transport electrification strategies required.
- The impact of regenerative breaking as a future technological advancement which can decrease city route electricity consumption was briefly highlighted in the third case study. Recently published works [29]–[32] have investigated the use of intelligent control algorithms to enhance the driving strategies, also with the objective of decreasing losses due to frequent breaking in urban settings. The incorporation of such algorithms is recommended for incorporation in this model in future follow-up work, in order to analyze the cost-efficiency of acquiring these technologies on the design of the EB transport systems.
- The proposed model was developed to consider any type of on-route or off-route charging infrastructures with any techno-economic properties. However, in the performed case studies, only the two most common on-route charges commercially available were considered. It is recommended that follow-up work consider other newly emerging fast charging technologies [33]. On-site storage devices (which can be modeled as a generic off-route charging infrastructure in the proposed formulation), especially newly emerging technologies such as fuel cells 34] or flywheels [35], should also be considered in the design of public transport systems.

VI. CONCLUSION

In this study, a mathematical model for fully-electric public transportation networks was formulated, and MILP optimization was implemented to minimize the TOC of a public transport system. The generic nature of the model was guaranteed by allowing the consideration of any set of routes, different EB models, battery capacities, and different charging technologies as input for the model. In this sense, the model is versatile and can be used to optimize already existing systems or design new ones due to its generic formulation. Three case studies were used to validate the proposed model while demonstrating its universal applicability. First, the design of three individual routes with different characteristics was demonstrated. Then, a large-scale generic transport system with 180 routes, consisting of urban and suburban routes with varying characteristics was considered and the optimal design was obtained and analyzed in detail. Afterwards, the use of the proposed model for a long-term transport system planning problem was demonstrated by adapting the system to a 2030 scenario based on forecasted technological advancements. The proposed formulation was shown to be highly versatile in modeling a wide variety of components in an EB transport system and in achieving an optimal design with minimal TOC. Several recommendations for future work were made, including the incorporation of power grid-interactive designs for future transport systems, considering the interaction with other transport networks or EV parking lots, or the consideration of on-route charging through newly emerging technologies.

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