A novel fast-charging stations locational planning model for electric bus transit system

Xiaomei Wu [a], Qijin Feng [a], Chenchen Bai [b], Chun Sing Lai [a,c,*], Youwei Jia [d], Loi Lei Lai [a]

[a] Department of Electrical Engineering, School of Automation, Guangdong University of Technology, Guangzhou 510006, PR China
[b] Department of Statistics and Data Science, Southern University of Science and Technology, Shenzhen 518055, PR China
[c] Brunel Institute of Power Systems, Department of Electronic and Electrical Engineering, Brunel University London, London, UB8 3PH, UK
[d] Department of Electrical and Electronic Engineering, Southern University of Science and Technology, Shenzhen 518055, PR China
* Corresponding author: chunsing.lai@brunel.ac.uk

***Abstract*— With more electric buses, the optimal location of charging station plays an important role for bus electrification. This paper proposes a location planning model of electric bus fast-charging stations for the electric bus transit system, that takes the bus operation network and the distribution network into account. The model 1) simulates the operation network of electric buses thoroughly to obtain the charging demand of electric buses and 2) takes into account of the absorption capacity of distribution network and other constraints in the siting and capacity determination stage. The objective of the model is to minimize the sum of the construction cost, operation and maintenance costs, travel cost to charging stations, and the cost of power loss for charging stations at established bus terminus. The Affinity Propagation method is adopted to cluster the bus terminuses in order to obtain a preliminary number of charging stations. Subsequently, the Binary Particle Swarm Optimization algorithm is used to optimize the site selection and capacity. Finally, the model is applied to simulate and analyze the bus operation network of a coastal city in South China. The case study shows that the model can effectively optimize the layout of bus charging stations for the city.**

Keywords: Fast-charging station; location planning; affinity propagation; binary particle swarm optimization

Nomenclature			
Abbreviation		p_{gd}	Best position of global in BPSO
e-bus	Electric Bus	v_{id}	Particle velocity in BPSO
AP	Affinity Propagation algorithm	$d_{i,c}$	Distance from charging demand point i to fast-charging station c, km
BPSO	Binary Particle Swarm Optimization algorithm	$var1_{i,j,b,t}$	The operating state of e-bus b in route j of terminus i at the time of its t-th operation
GA	Genetic algorithm	$var2_{i,j,b,t}$	The charging state of e-bus b in route j of terminus i at the time of its t-th charging
SOC	State of Charge	$SOC1_{i,j,b,t}$	*SOC* of e-bus b in route j of terminus i at the time of its t-th departure
		$SOC2_{i,j,b,t}$	*SOC* of e-bus b in route j of terminus i at the time of its t-th arrival
Parameters		$E_{i,j}$	Energy consumption of route j operated by the i-th terminus, kWh
D	Dimension of the particles	$E_{i,c}$	Energy consumption from bus terminus i to charging station c, kWh
c_1, c_2	Learning factors	$TD_{i,j,b,t}$	Dwelling time of e-bus b in route j operated by terminus i at the time of its t-th dwell, minute
λ	The damping factor	$TC_{i,j,b,t}$	Charging time of e-bus b in route j operated by terminus i at the time of its t-th dwell, minute
ω	Inertia weight	$T_{i,c}$	Driving time from bus terminus i to charging station c, minute
P	Charging power of the equipped charging facilities	$e_{i,j,b,t}$	Electric energy obtained of e-bus b in route j of terminus i at the time of its t-th charging, kWh
$C_{battery}$	Battery capacity of e-bus, kWh	NSD_c	Number of charging spots required for daytime charging of fast-charging station c
u	Energy consumption per kilometer, kWh/km	TCD_c	Effective charging time of fast-charging station c during the daytime, minute
α	Fluctuation coefficient of charging demand	$\Delta tc_{i,j,b}$	Time required for e-bus b in route j operated by terminus i to be fully charged at night, minute
k_s	Operation simultaneous rate of charging facilities	TCN_c	Effective charging time of fast-charging station c at night, minute
k_{eff}	Charging efficiency of the charging facility, %	NSN_c	Number of charging spots required for night charging of fast-charging station c
TR_j	the operation time of route j, minute	NS_c	Number of charging spots to be built for the fast-charging station c
TS_j	the spacing interval of route j, minute	NT_c	Number of transformers in the charging station c

SOC_{max}	Maximum *SOC* of e-bus battery	$n_{c,i}$	Number of charging times of terminus *i* of charging station *c*
SOC_{min}	Minimum *SOC* of e-bus battery	$Y_{c,n}$	State variable representing the connection between charging station *c* and node *n* in distribution network.
$L_{i,j}$	Length of route *j* operated by the *i*-th terminus, km	$L_{c,n}$	Length of the power distribution line connecting charging station *c* to node *n* of distribution network, km
η_b	Assuming scaling factor, %	x_{id}	State variable representing whether the bus terminus is the charging station or not
g_t	Electricity price of charging, ¥/kWh	NB_j	Number of e-buses of route *j*
N	Number of distribution network node	NI_c	Number of charging demand points belonging to the same cluster of fast-charging station *c*
μ	Charging capacity redundancy of the fast-charging station	NJ_i	Number of bus routes operated by charging demand point *i*
λ_d	Influencing factor on the operation routes	NT_b	Number of arrivals of e-bus b
r_0	Discount rate, %	NC	Number of charging stations
γ	Operating life of the charging station, year	C_{1c}	Equipment and installation cost of charging station *c*, ¥
p_1	Unit price of the charging facility, ¥	C_{2c}	Construction cost of power distribution line, ¥
ω_c	Construction cost of charging station *c*, ¥	C_{3c}	Operation and maintenance cost of charging station *c*, ¥
α_{cn}	Equipment and installation cost of power distribution line per kilometer, ¥/km	C_{4c}	Travel cost of e-bus to charging station *c*, ¥
p_2	Unit price of the transformer, ¥	C_5	Power loss cost, ¥
g_p	Average tariff including tax	P_{loss2}	Active power loss after fast-charging station access, kW
L	Service radius of fast-charging station, km	U_n	Voltage magnitude of bus *n*, kV
U_n^{min}, U_n^{max}	Upper/lower margins of voltage magnitude, kV	$P_{c,n}$	Charging power of the charging station *c* access node *n* of distribution network, kW
NS_{min}	Minimum number of charging facilities		
NS_{max}	Maximum number of charging facilities	Sets and Indices	
P_n^{max}	Maximum power allowed for node *n* of distribution network, kW	$\vec{x}_i$	The set of bus terminus
P_{loss1}	Active power loss before fast-charging station access, kW	$S(i, j)$	The set of "suitability"
P_n	Load power of node *n* of distribution network, kW	$R(i, k)$	The set of "responsibility"
		$A(i, k)$	The set of "availability"
Variables		b	The e-buses index, where b=1, 2, ..., NB_j
F	Objective function	c	The fast-charging station index, where c=1, 2, ..., NC
p_{id}	Best position of particle in BPSO		

1. Introduction

With the depletion of fossil energy resources, increased environmental pollution, promoting low-carbon economy and reduction of carbon emissions that attract people's awareness of decarbonization and the willingness to deploy smart cities worldwide; smart energy and smart transportation are the two most essential components in smart cities [1]. As a major energy producer and consumer, China has been committed to energy transition and reducing carbon emissions [2]. Electric vehicles, as a new form of energy transportation, are considered as one of the solutions for China to reduce its carbon emissions and dependence from oil. Electric buses (E-buses) play an important role in urban transportation in many cities. By analyzing the life cycle costs and carbon emissions of different type of e-buses, some studies point out that electric vehicles produce less carbon emissions than the traditional ones, which is important to improve air quality and reduce environmental pollution [3,4]. With the development of new energy and charging management technologies, the environmental friendliness of electric vehicles is expected to be further strengthened [5,6]. In addition, the use of electric vehicles can also contribute to the consumption of new energy and the stable operation of distribution network [7]. For example, electric vehicles can be used to mitigate fluctuations in photovoltaic output in the low-voltage grid [8]. The demand response of electric vehicles can also be used to smooth the wind power and limit the ramp rate, so as to solve the problem of high penetration of wind farms [9]. Some studies had shown that electric vehicles can be used as portable generators, which supply power to critical loads in emergency condition by using Vehicle-to-Grid technology [10].

However, with the growth of electric vehicles, problems such as lack of, and sub-optimal placements of charging infrastructure are gradually exposed [11]. To better understand the interaction between the promotion of electric vehicles and construction of charging infrastructure, China has issued a series of policies to promote the development of a national charging network [12].

Therefore, effective charging station deployment may help avoiding non-economic investment and further promoting the penetration of electric vehicles in the market. Most of the current studies focus on private electric vehicles or taxis, and fewer consider the optimization of e-bus charging stations. For example, Yang et al. described the decision-making process of electric vehicle users and the driving characteristics of electric vehicles, and further analyzed electric vehicle charging demand variation curve [13]. Hosseini et al. proposed a Bayesian Network model that considered uncertainty, quantitative factors and qualitative factors, further assessed the site selection of charging stations from a sustainability and technical point of view [14]. From the perspective of distribution network, Wang et al. described a distributed test network model, which combined active and reactive power optimization methods to determine the optimal placement of charging stations to reduce power losses [15]. From the driver's point of view, according to the trip success ratio of electric vehicles, Alhazmi et al. selected the charging stations to optimize the trip success ratio from the existing candidate charging stations [16]. Morro-Mello et al. also proposed a method to optimize the allocation of fast-charging stations for urban electric taxis which met the planning requirements of all urban planners [17].

Compared with the uncertain usage of private cars and taxis, e-bus has a fixed operation route and a systemic daily operation schedule. This is not only beneficial to the countries to reduce carbon emissions as well as the transition to low-carbon energy, but also to the charge of grid for V2G scheduling. From the technological development history of e-buses in China, e-buses occupy a large share of the Chinese new energy vehicle market and will play a key role in urban electrified transportation [18]. From the recent announcements of the National Development and Reform Commission and Ministry of Industry and Information Technology, it is suggested that China will vigorously promote electrification of public sector in the future, including public transportation, sanitation vehicles, and taxis [19-21]. Mahmoud et al. reviewed the development history of e-bus technology and pointed out that electrification of public buses in cities is feasible [22]. Gao et al. indicated that high-power charging technology could make the service reliability of e-buses in operation consistent with that of traditional diesel buses [23].

Thus, the electrification of urban bus network is important for transport systems. The construction of charging infrastructure at existing bus terminus is very important as e-buses are getting popular. To date, there are few literatures documenting the optimization of charging infrastructure for e-buses. Some of these studies are briefly summarized in Table 1. Bi et al. proposed a framework of multi-objective optimization model based on life cycle assessment for siting the location of wireless charger in multi-route e-bus transit system [24]. Ke et al. studied the bus transit system in Penghu, the impact of day and night charging on the construction cost of the e-bus transit system was examined to improve the practicability of e-buses [25]. He, et al. proposed a mathematical model for the optimal planning of fast-charging stations to alleviate the problem of high charges caused by high-speed charging, and applied the model to the public transport system in Salt Lake City. The optimization results showed that the fast-charging stations could be built at on-street bus stops that are shared by many bus routes [26]. To determine which bus stop is selected to build charging station, Wang et al. used a linear programming relaxation algorithm, and multiple backtracking and greedy algorithms to minimize the total installation cost of the charging station [27]. Xylia et al. minimized the total costs or the total energy consumption of the electrification e-bus system, and the charging stations were deployed at major transport hubs [28]. Rogge et al. studied the cost-optimized planning of depot charging battery bus fleets and their corresponding charging infrastructure. The total cost of electrification operation is minimized and the grouping genetic algorithm and mixed integer nonlinear programming are adopted to solve the problem [29]. Lajunen also pointed out that, compared with charging at night and charging at bus stops along the way, charging stations at bus terminuses are cheaper and more suitable for bus electrification during the whole life cycle [30]. However, the study of Rogge et al. assumed that all bus terminuses should be equipped with charging stations, which would only lead to high investment costs and redundant equipment including transformers and power converters [31].

Therefore, based on the above literature review, this paper proposes an optimization model of e-bus fast-charging station considering the bus transit system and the power distribution network. The contributions of this paper are as follows:

1) With the Affinity Propagation (AP) clustering algorithm, we proposed clustering the adjacent terminuses into the same class according to the geographical location of each bus terminuses in order to share resources. AP is a clustering algorithm based on the information transfer mechanism between data points, which can avoid determining the number of clusters and setting the initial values.

2) A real-life bus dispatching schedule is adopted to simulate daily charging load for a city's bus transit system.

3) The optimal cost model of charging station is proposed, where the bus transit system and power distribution network are considered as well.

4) With binary particle swarm optimization, we optimize the deployment of fast-charging stations due to discrete site selection, also the charging capacities such that the total bus transit system cost is minimized.

5) A methodology is developed to solve the fast-charging stations deployment problem. The convergence behavior and the total cost are investigated.

The remainder of the paper is organized as follows. Section 2 provides operating characteristics of e-buses and the clustering of bus stations. Section 3 formulates the optimization model, followed by a numerical study to demonstrate the effectiveness of the proposed model in Section 4. Section 5 concludes the paper.

2. Problem description and assumptions

In this section, the description and assumptions regarding bus routes and fast-charging stations of an e-bus system are presented. In addition, an analytical model for clustering bus stations is proposed.

2.1 *Operating characteristics of electric buses*

Assuming a bus transit system is with multiple bus routes. Then each bus route has a fixed loop route with the same start point and end point. Due to the operational requirements of e-buses, they require larger onboard batteries than that of other types of electric cars, so even using fast-charging mode, it will take dozens of minutes to several hours for charging up to a reasonable amount of stored energy. The Bloomberg report pointed out that although pantograph chargers and wireless charging have low on-board battery capacity requirements for e-bus, they are nevertheless less flexible, limited by space and local policy [32]. Both technologies are currently expensive. Therefore, it is more realistic to use fast-charging technology. The e-buses can only be recharged near the terminus in the period of waiting for the next departure only after they have run the operating routes. There is a large number of bus terminuses. The charging demand of each station is affected by the number of e-buses, time headway and operating time of each route. The

Table 1 Research on e-bus charging stations deployment

Literature		Zicheng Bi et al. [24]	Bwo-Ren Ke et al. [25]	Yi He et al. [26]	Xiumin Wang et al. [27]	Maria Xylia et al. [28]	Matthias Rogge et al. [29]	This work
Location of study		University of Michigan	Penghu, Taiwan	Salt Lake City, Utah	Qingdao, China	Stockholm, Sweden	European Cities: Aachen, German; Roskilde, Danish	Yangjiang, China
Optimization method		Genetic algorithm	Genetic algorithm	Mixed integer linear programming	Linear programming relaxation algorithm; Multiple backtracking and greedy algorithm	Mixed integer linear programming	Grouping genetic algorithm; Mixed integer non-linear programming	Affinity propagation algorithm; Binary particle swarm optimization
Charging station deployment		Deploy large-scale wireless charging infrastructure at bus stops	Build charging station in parking lots	Install fast-charging stations at an on-street bus stop or a bus terminal	Install electric vehicle charging stations at selected bus stops	Deploy charging stations at major transport hubs	Plan depot charging station	Deploy fast-charging station in bus terminus
Bus dispatching schedule		Y	Y	Y	Y	N	N	Y
Charging station sharing for different bus routes		N	N	N	Y	Y	N	Y
Objective function	Construction cost of power distribution line	N	N	N	N	N	N	Y
	Operation and maintenance cost of charging station	N	N	N	N	Y	N	Y
	Travel cost of e-bus to charging station	Y	Y	N	N	Y	Y	Y
	Power loss cost	N	N	N	N	N	N	Y
	Greenhouse gas emissions	Y	N	N	N	N	N	N
	Installation cost of energy storage systems	N	N	Y	N	N	N	N
Constraints	Bus voltages	N	N	N	N	N	N	Y
	Line flows	N	N	N	N	N	N	Y

investment cost will be too high if charging stations are built at each bus terminus. Also, the equipment in the station is often redundant. Therefore, by clustering the adjacent bus terminuses and building relatively centralized fast-charging station, the investment of the fast-charging station can be reduced, and the usage effectiveness can be improved.

2.2 *Affinity Propagation algorithm*

Affinity Propagation (AP) is a clustering algorithm based on the information transfer mechanism between data points [12]. This algorithm can avoid determining the number of clusters and the sensitive issue setting the initial values, which pose in traditional clustering algorithms such as K-mean [33]. In this paper, each bus terminus is regarded as potential clustering centers. According to the geographical location information of the terminuses, the similarity set S between the terminuses is constructed, where the similarity $S(i, j)$ indicates how well the terminus with index j is suited to be the exemplar for data point i.

$$S(i,j) = -\left\| \overrightarrow{z_i} - \overrightarrow{z_j} \right\|^2 \tag{1}$$

The terminuses with larger values of $S(k, k)$ are more likely to be chosen as an exemplar. These values are referred to as "preferences". The iterative process is to perform an exemplar competition according to the "availability" and "responsibility" between the terminuses. The "responsibility" $R(i, k)$, sent from data point i to candidate exemplar point k, reflects the accumulated evidence for how well-suited point k is to serve as the exemplar for point i, taking into account other potential exemplars for point i. The "availability" $A(i, k)$, sent from candidate exemplar point k to point i, reflects the accumulated evidence for how appropriate it would be for point i to choose point k as its exemplar, taking into account the support from other points that point k should be an exemplar. The responsibilities are computed using the following rules [34]:

$$R_{t+1}(i,k) = \begin{cases} S(i,k) - \max\limits_{j \neq k} \left\{ A_t(i,j) + R_t(i,j) \right\}, i \neq k \\ S(i,k) - \max\limits_{j \neq k} \left\{ S(i,j) \right\}, i = k \end{cases} \tag{2}$$

$$A_{t+1}(i,k) = \begin{cases} \min\left\{ 0, R_{t+1}(k,k) + \sum\limits_{j \neq \{i,k\}} \max\left\{ 0, R_{t+1}(j,k) \right\} \right\}, i \neq k \\ \sum\limits_{j \neq k} \max\left\{ 0, R_{t+1}(j,k) \right\}, i = k \end{cases} \tag{3}$$

The damping factor λ is introduced to avoid numerical oscillation and adjust the convergence rate of AP clustering algorithm in the iterative updating process. Then the above equations are updated as follows:

$$R_{t+1}(i,k) = (1-\lambda) \cdot R_{t+1}(i,k) + \lambda \cdot R_t(i,k) \tag{4}$$

$$A_{t+1}(i,k) = (1-\lambda) \cdot A_{t+1}(i,k) + \lambda \cdot A_t(i,k) \tag{5}$$

The clustering division of the terminuses can be obtained through the AP clustering algorithm. Since the fast-charging site selection is discrete, Binary Particle Swarm Optimization algorithm is used to solve the optimization problem. Based on the results of clustering, the binary code is used to generate initial particle populations. Each population represents a combination mode, and the fast-charging stations in each combination mode are selected from the terminuses. The advantage is that it can ensure that each charging station and its charging demands can be classified into the same category, in addition to this, the combination of fast-charging station sites updated in each iteration is guaranteed to be a feasible solution, which reduces the search space.

In this paper, $\vec{x}_i$ in BPSO represents the i-th particle position, and each particle represents a solution of the planning problem.

$$\vec{x}_i = \left[x_{i1}, x_{i2}, \cdots, x_{id}, \cdots, x_{iD} \right] \tag{6}$$

where

D - the dimension of the particles, which corresponds to the number of terminuses of each cluster,

x_{id} - indicates whether the i-th particle selects the d-th terminus as the fast-charging station, and its values are {0,1}. Its particle velocity is updated as follows [35] :

$$v_{id}^{t+1} = \omega \cdot v_{id}^{t} + c_1 \cdot rand\left(p_{id}^{t} - x_{id}^{t} \right) + c_2 \cdot rand\left(p_{gd}^{t} - x_{id}^{t} \right) \tag{7}$$

where

ω - inertia weight,

c_1, c_2 - learning factors,

rand( ) - a random positive number between 0 and 1,

p_{id} - best position of particle in BPSO,

p_{gd} - best position of global in BPSO.

After updating, each particle velocity v_{id} will be mapped to the probability value of x_{id} by the *sigmoid*( ) function, and its position will be updated by Eq. (9) [36]:

$$Sig(v_{id}) = \frac{1}{1+\exp(-v_{id})} \tag{8}$$

$$x_{id} = \begin{cases} 1 & rand(\ ) \le Sig(v_{id}) \\ 0 & otherwise \end{cases} \tag{9}$$

where

$Sig(v_{id})$ - a sigmoid limiting transformation which represents the probability in which the position x_{id} takes 1.

3. Model Formulation

In the following section, a mathematical program is developed to optimize the deployment of fast-charging stations, as well as the capacity in order to minimize the total cost. The detailed model solution and optimal flow chart is shown in Fig. 1.

3.1 *Capacity model of electric bus fast-charging station*

Compared with other types of electric vehicles, e-buses have a fixed operation mode. Therefore, in this paper, we obtain the spatial-temporal distribution characteristics of buses according to its operation scheduling plan, and simulate the operational task according to the spatial-temporal distribution characteristics. From the characteristics of the bus route, to ensure the demand of the route, the number of e-buses needs to be reasonably configured. The number of e-buses required for route j is determined by Eq. (10):

$$NB_j = ceil\left(\frac{TR_j + 60\left(SOC_{max} - SOC_{min}\right)C_{battery}}{TS_j}\right) \tag{10}$$

where

NB_j - number of e-buses that need to be configured for route j,

TR_j - running time of route j, minute,

TS_j - spacing interval of route j, minute,

$C_{battery}$ - battery capacity of e-bus,

SOC_{min} - minimum SOC of e-bus battery,

SOC_{max} - maximum SOC of e-bus battery,

$ceil(\,)$ - function for rounding up to an integer.

The simulation model needs to assume some state variables to track the e-bus state throughout the whole process. Assuming that $var1_{i,j,b,t}$, $var2_{i,j,b,t}$, $SOC1_{i,j,b,t}$, and $SOC2_{i,j,b,t}$ are the operating state, the charging state, the state of charge when the e-bus is departing, and the state of charge when the e-bus is arriving at bus b in route j of terminus i at the time of its t-th departure or arrival, respectively.

1) The first bus departure is scheduled according to the operation schedule, at this moment $SOC_{1,i,j,b,t}$=1 and $var_{1,i,j,b,t}$=1.

2) After the TR_j time, the e-bus arrives at the terminus, at this moment $var1_{i,j,b,t}$ =0, the arrival time should be recorded and $SOC2_{i,j,b,t}$ are recorded as follows:

$$SOC2_{i,j,b,t} = SOC1_{i,j,b,t} - \frac{E_{i,j}}{C_{battery}} \tag{11}$$

where the energy consumption of route j operated by the i-th terminus:

$$E_{i,j} = uL_{i,j}\lambda_d \tag{12}$$

where

u - energy consumption per kilometer, kWh/km,

$L_{i,j}$ - length of route j operated by the i-th terminus, km,

λ_d - influencing factor on the operation routes, for example, slope, rugged degree, etc., which together named as a comprehensive factor, and generally taken between 1.1-1.3 [6].

3) According to Eq. (13), if the e-bus needs to be charged, setting $var2_{i,j,b,t}$ at 1; otherwise, setting as 0 and wait for the next departure time:

$$SOC2_{i,j,b,t} - \frac{E_{i,j} + E_{i,c}}{C_{battery}} \le SOC_{min} \tag{13}$$

where

$E_{i,c}$ - energy consumption from bus terminus i to charging station c, kWh,

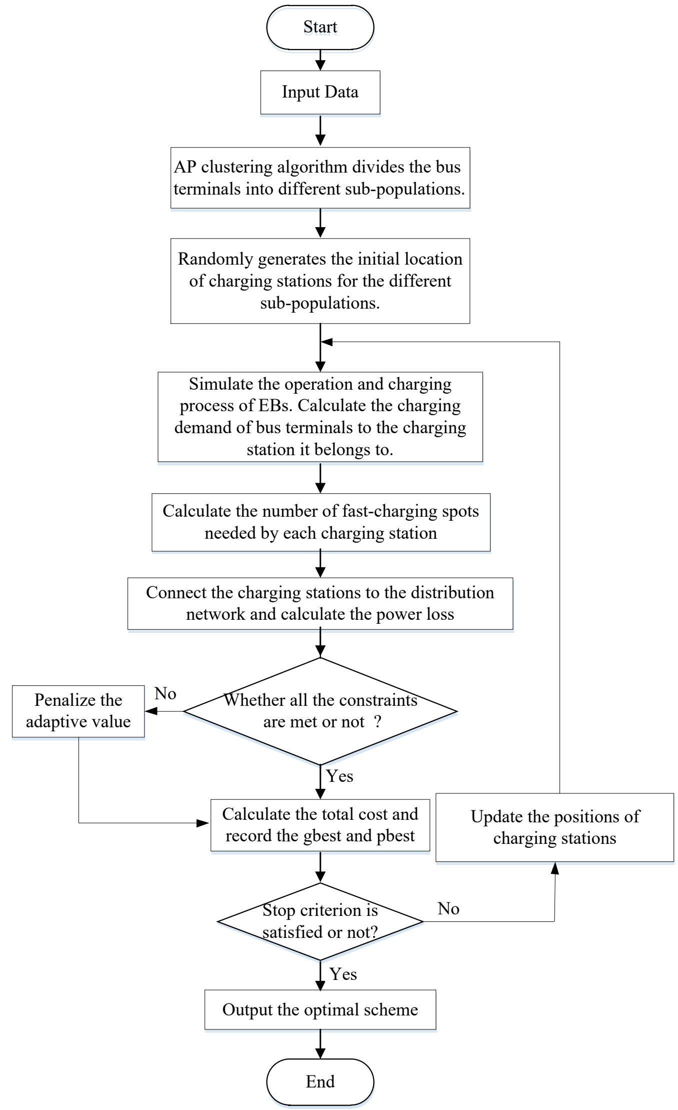


Fig.1. AP-BPSO algorithm flow chart

4) If the e-bus needs to be charged, the charging time for the e-bus is calculated according to Eq. (14). Meanwhile, in order to ensure that the SOC of the e-bus can meet the next operation task and not exceed the spacing interval, the charging time needs to meet the constraint of Eq. (15). The energy obtained from charging is given by Eq. (16).

$$TC_{i,j,b,t} = \begin{cases} \dfrac{60\left(SOC_{max} - SOC2_{i,j,b,t}\right)C_{battery} + E_{i,c}}{P} & if \quad var2_{i,j,b,t} = 1 \\ 0 & else \end{cases} \tag{14}$$

$$\begin{cases} TC_{i,j,b,t} \ge \dfrac{60\left(SOC_{min} - SOC2_{i,j,b,t}\right)C_{battery} + E_{i,j} + E_{i,c}}{P} \\ TC_{i,j,b,t} \le TD_{i,j,b,t} - 2T_{i,c} \end{cases} \tag{15}$$

$$e_{i,j,b,t} = \frac{TC_{i,j,b,t} \cdot P}{C_{battery} \cdot 60} \tag{16}$$

where

$TC_{i,j,b,t}$ - charging time of e-bus b in route j operated by terminus i at the time of its t-th dwell, minute,

P - charging power of the equipped charging facilities, kW,

$TD_{i,j,b,t}$ - dwelling time of e-bus b in route j operated by terminus i at the time of its t-th dwell, minute

$T_{i,c}$ - driving time from bus terminus i to charging station c, minute,

$e_{i,j,b,t}$ - electric energy obtained of e-bus b in route j of terminus i at the time of its t-th charging, kWh.

5) After a period of $TD_{i,j,b,t}$, it is time for departure, at this moment $SOC1_{i,j,b,t}$ is:

$$SOC1_{i,j,b,t}=\begin{cases} SOC2_{i,j,b,t}+e_{i,j,b,\mathrm{t}}-\dfrac{2E_{i,c}}{C_{battery}} & if \quad var2_{i,j,b,t}=1 \\ SOC2_{i,j,b,t} & else \end{cases} \tag{17}$$

6) Repeat Steps 2) to 5) until all e-buses, routes and terminuses have been traversed to obtain the total charging demand and effective charging time of each bus terminus during the daytime operation. The number of charging spots required for charging during the day is as follows:

$$NSD_c = ceil\left(\frac{\sum_{i=1}^{NI_c}\sum_{j=1}^{NJ_i}\sum_{b=1}^{NB_j}\sum_{t=1}^{NT_b} e_{i,\mathrm{j,b,t}}\cdot(1+\mu)}{TCD_c\cdot P\cdot k_s\cdot k_{eff}}\cdot\alpha \right) \tag{18}$$

where

NSD_c - number of charging spots required for daytime charging of fast-charging station c,

NI_c - number of charging demand points belonging to the same cluster of fast-charging station c,

NJ_i - number of bus routes operated by charging demand point i,
NT_b - number of arrivals of e-bus b,

μ - charging capacity redundancy of the fast-charging station,

TCD_c - effective charging time of fast-charging station c during the daytime, minute,

k_s - operation simultaneous rate of charging facilities,

k_{eff} - charging efficiency of the charging facility, %,

α - fluctuation coefficient of charging demand.

The period from the end of operation on one day to the beginning of operation on the next day is the charging time at night. During this period, the number of charging spots should meet the operation requirements of all the e-buses on the next day. According to the SOC, when the buses are fully charged, the number of charging spots required for night charging is as follows:

$$NSN_c = ceil\left(\frac{\sum_{i=1}^{NI_c}\sum_{j=1}^{NJ_i}\sum_{b=1}^{NB_j}\Delta tc_{i,j,b}}{TCN_c} \right) \tag{19}$$

where

NSN_c - number of charging spots required for night charging of fast-charging station c

$\Delta tc_{i,j,b}$ - time required for e-bus b in route j operated by terminus i to be fully charged at night, minute

TCN_c - effective charging time of fast-charging station c at night, minute.

The number of charging facilities to be built for the fast-charging station c is given as follows:

$$NS_c = \max(NSD_c, NSN_c) \tag{20}$$

3.2 *Deployment model of electric bus fast-charging station*

The objective function for e-bus fast-charging station planning is to minimize the total cost of charging station.

$$\min F = \sum_{c=1}^{NC}\left(C_{1c}+C_{2c}+C_{3c}+C_{4c}\right)+C_5 \tag{21}$$

where

NC - number of charging stations,

C_{1c} - equipment and installation cost of charging station c, ¥

C_{2c} - construction cost of power distribution line, ¥

C_{3c} - operation and maintenance cost of charging station c, ¥

C_{4c} - travel cost of e-bus to charging station c, ¥

C_5 - power loss cost, ¥.

$$s.t. \quad NS_{min} \le NS_c \le NS_{max} \tag{22}$$

$$d_{i,c} \le 0.5L \tag{23}$$

$$\sum_{n=1}^{N} Y_{c,n} = 1 \tag{24}$$

$$U_n^{min} < U_n < U_n^{max}, n=1,2,\cdots,N \tag{25}$$

$$P_{c,n}+P_n \le P_n^{max} \tag{26}$$

where

$d_{i,c}$ - distance from the charging demand point i to the fast-charging station c, km,

L - service radius of fast-charging station, km,

$Y_{c,n}$ - state variable representing the connection between charging station c and node n in distribution network. If the charging station c is connected to node n of the distribution network, then Y_{cn}=1. Otherwise, it is 0,

N - number of distribution network node,

U_n - voltage magnitude of node n of distribution network,

U_n^{min} and U_n^{max} - upper and lower margins of voltage magnitude of node n of distribution network, kV

$P_{c,n}$ - charging power of the charging station c access node n of distribution network, kW

P_n - load power of node n of distribution network, kW

P_n^{max} - maximum power allowed for node n of distribution network, kW.

For the technical constraints, Eq. (22) shows that when the charging facilities are configured, the limitation of the occupied area should be taken into account. The limitation of the occupied area is converted into the maximum number of charging facilities that can be installed in the station. Eq. (23) shows that in order to satisfy the charging reliability, the distance from the charging demand point to the fast-charging station needs to be met. Eq. (24) shows that each charging station can only access to one distribution network node. Eq. (25) and Eq. (26) show that the constraints of the distribution network include load constraints and voltage constraints.

Each cost is calculated as follows:

1) Equipment and installation cost of charging station

$$C_{1c} = \left(NS_c \cdot p_1 + NT_c \cdot p_2 + \omega_c\right)\frac{r_0 \cdot \left(1+r_0\right)^{\gamma}}{\left(1+r_0\right)^{\gamma}-1} \tag{27}$$

where

r_0 - discount rate, %,

γ - operating life of the charging station, year,

NS_c - number of charging facilities at the charging station c,

p_1 - unit price of the charging facility, ¥,

NT_c - number of transformers in the charging station c,

p_2 - unit price of the transformer, ¥,

ω_c - construction cost of charging station c, ¥.

2). Construction cost of power distribution line

$$C_{2c} = \alpha_{cn} Y_{c,n} L_{c,n} \frac{r_0 \cdot \left(1+r_0\right)^{\gamma}}{\left(1+r_0\right)^{\gamma}-1} \tag{28}$$

where

α_{cn} - equipment and installation cost of power distribution line per kilometer, ¥/km,

$L_{c,n}$ - length of the power distribution line connecting charging station c to node n of the distribution network, km.

3). Operation and maintenance cost of charging station

The calculation of the annual operation and maintenance cost is given as follows:

$$C_{3c} = \left(C_{1c} + C_{2c}\right)\cdot \eta_b \tag{29}$$

where

η_b - assuming scaling factor, %.

4). Travel cost to charging station is given as below:

$$C_{4c} = 365\sum_{c=1}^{NC}\sum_{i=1}^{NJ_c} 2 g_t E_{i,c} n_{c,i} \tag{30}$$

where

g_t - electricity price of charging, ¥/kWh,

$n_{c,i}$ - number of charging times of terminus i of charging station c.

5). Power loss cost

After the charging station is connected to the distribution network, the active power loss of the distribution network will increase. The increased annual power loss cost is shown as follows:

$$C_5 = g_p \int_0^{8760} \left[P_{loss2}\left(\mathrm{t}\right) \text{-} P_{loss1}\left(\mathrm{t}\right)\right] dt \tag{31}$$

where

g_p - average tariff including tax,

P_{loss1} - active power loss of distribution network before fast-charging station access, kW

P_{loss2} - active power loss of distribution network after fast-charging station access, kW.

4. Results and discussion

A numerical study to demonstrate the effectiveness of the proposed model is given. The numerical study is based on a real bus transit system in urban area Yangjiang City, which is a coastal city in South China.

4.1 *Spatio-temporal distribution of buses*

A bus transit system with 26 bus routes is utilized in this numerical study. The routes of the bus transit system cover 510.8 km of road segments in urban and suburb areas of Yangjiang City. The 26 bus routes serve 388 bus stops, where 34 terminuses are included. In this paper, only the urban area of the city is considered, where the geographical distribution of the terminuses is shown in Fig. 2. The simulation parameters utilized for bus dispatching schedule is listed in Table 2.

For simplicity, it is assumed that the e-buses used for the 26 bus routes are with the same model. In the future, the whole subnetwork in Fig. 2 will be served by the Yutong E6 e-bus with an on-board battery capacity of 85.85 kWh, and the charging power is 120 kW. The proposed optimization model can help Yangjiang city to determine the locations and number of fast-charging stations, the numbers of charging spots within fast-charging stations, and the cost of the electrified bus network.

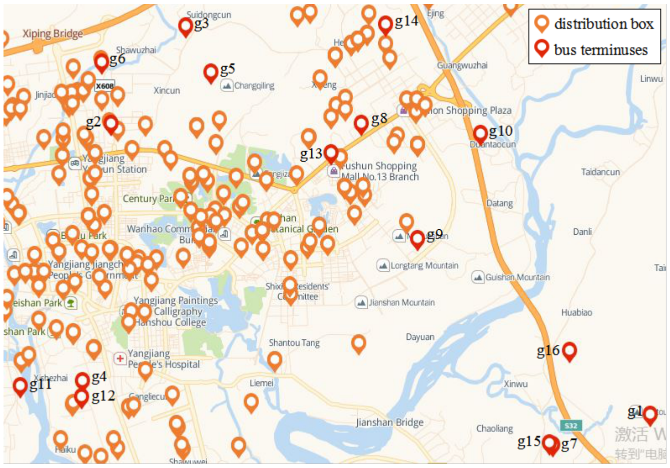


Fig.2. Schematic diagram of the planning area

Table 2 Bus dispatching schedule

Station	Route	Number of buses	First bus	Last bus	Time headway (min)	Route length (km)
g1	2	7	7:00	20:00	20	20
g2	2	7	7:00	20:00	20	20
	3	15	6:10	21:15	15	27
	5	3	6:35	18:35	60	23
	8	22	6:05	22:00	9	30
	11	2	7:15	19:00	180	29
	12	9	6:05	21:00	13	25
	14	3	7:30	22:30	40	12
g3	7	2	8:00	16:30	180	22
	4	7	7:00	20:00	30	23.5
g4	6	2	6:55	17:35	140	21
g5	9	1	8:30	17:30	390	30
g6	10	1	7:30	17:00	120	8.3
g7	25	1	7:30	17:30	120	7
	26	1	7:30	17:30	120	3
g8	1	5	7:00	20:00	40	21
g9	4	7	7:00	20:00	30	23.5
g10	6	2	6:55	17:35	140	21
g11	7	2	8:00	16:30	180	22
g12	10	1	7:30	17:00	120	8.3
g13	15	2	9:40	19:30	80	15
	20	1	7:00	17:00	480	26
g14	16	1	9:00	15:30	180	21
g15	18	1	10:20	13:50	120	10
g16	26	1	7:30	17:30	120	3

*Note: One bus route has two terminuses. Some terminuses are far away from the planned area, which is not included in the Table.

4.2 *Optimized deployment of e-bus fast-charging stations*

The AP clustering algorithm is used to obtain the charging demand location of each terminus and the number of fast-charging stations needed to be built for the bus network. Based on the model proposed in Section 3, the optimal solution is obtained of e-bus fast-charging stations by the BPSO algorithm. As a result, the planning scheme obtained by the proposed optimization model is 4 fast-charging stations to serve 16 bus terminuses and 26 bus routes. The detailed charging station planning scheme is shown in Table 3. The optimal cost of the model is reported in Table 4. The location and service of the fast-charging stations is shown in Fig. 3, where the selected bus terminus is marked blue. The variation of the *SOC* of e-buses in the daytime operation is shown in Fig. 4. Due to the large number of e-buses involved in the study, only the bus route 8 is taken as an example, and the rest of the e-buses are similar.

Table 3 Planning scheme of fast-charging stations

Terminuses used for charging stations	Number of fast-charging spots	Served e-buses	Number of charging times	Charging demand (kWh)
g1	2	11	18	767
g2	9	72	171	7554
g9	3	18	29	1226
g12	1	5	5	183

Table 4 Cost of fast-charging stations

Result	Value (¥[1] × 10^6)
Equipment and installation cost	0.442
Distribution line construction cost	0.096
Operation and maintenance cost	0.061
Total travel cost	0.093
Total power loss cost	0.114

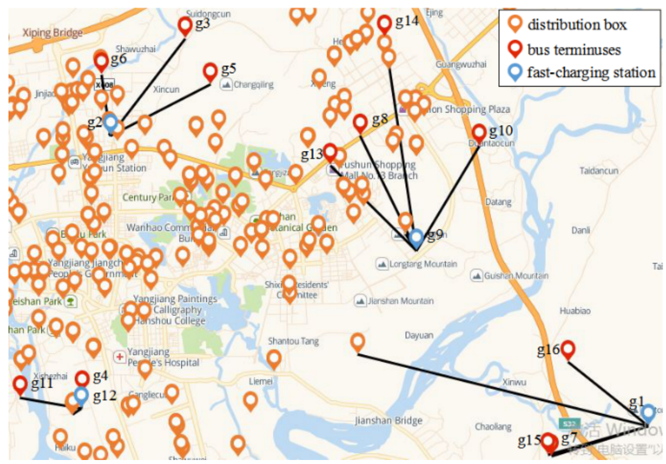


Fig. 3. Deployment of fast-charging stations

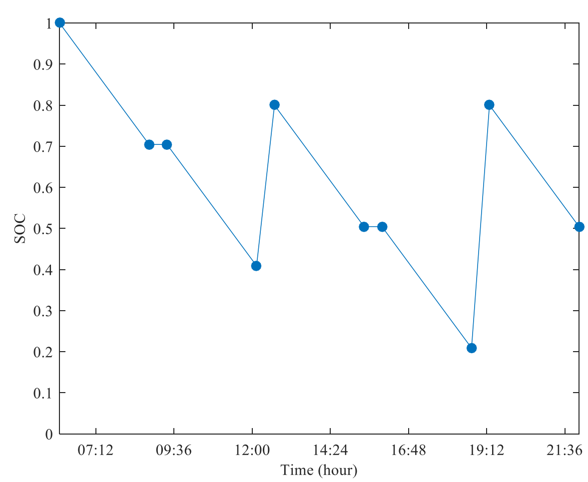
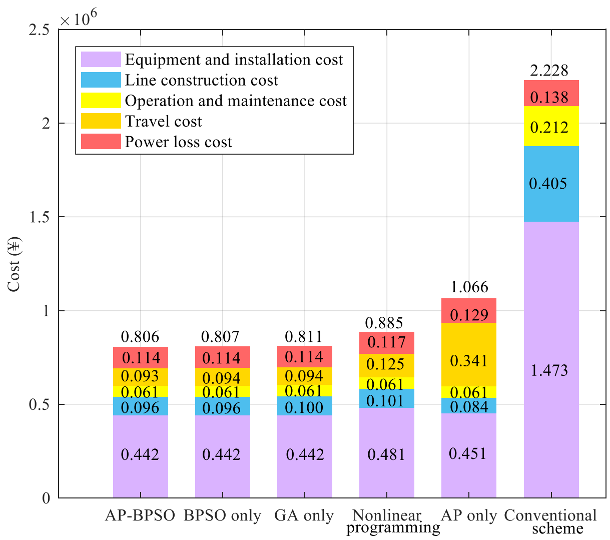


Fig. 4. Changes in *SOC* of bus route 8

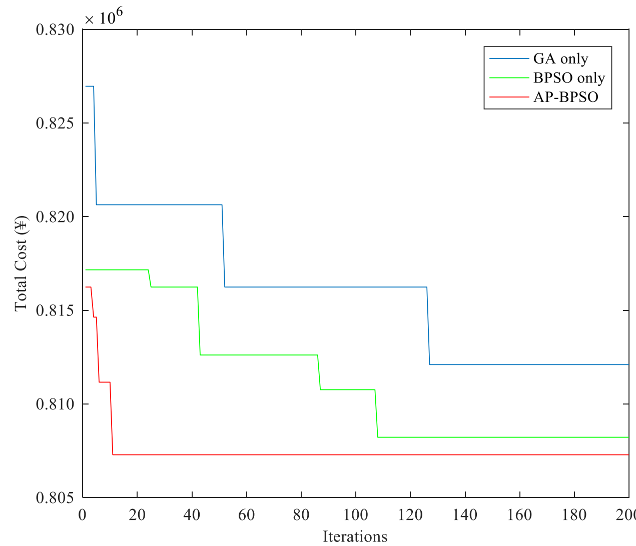
[1] Chinese RMB ￥1 ≈USD $0.1501

4.3 *Comparison of different optimization planning methods*

To present the economic benefits of the proposed optimization model, a comparison of placing fast-charging stations at selected terminuses is conducted as shown in Fig. 5a. Conventional planning scheme is to build charging stations in each bus terminus. Although the travel cost on the way to charging station should not be considered in conventional planning scheme, other costs might much higher and the equipment will be redundant because fast-charging stations are built in each bus terminus. For AP clustering only, the obtained location of fast-charging stations is the closest to other bus terminuses. But the difference in the number of routes and e-buses operated by different terminuses is ignored, resulting in a larger total travel cost. It can be seen that the deployment of charging stations cannot be determined only by the distance between bus terminuses. The calculated costs of GA algorithm and BPSO algorithm are slightly higher than that of proposed method in this paper. The convergence of these three algorithms is compared, as shown in Fig. 5b. The proposed method has a faster rate of convergence and a reduced total cost than BPSO algorithm. The reason is that the terminuses have been classified before optimization. After the classification, the number of terminuses within each class decreases. When the BPSO algorithm is used for each class, its optimization range becomes smaller. BPSO needs to be calculated several times for several classes, but the calculation speed is shorter than that of non-clustering. Therefore, for the electrification of public transport network in Yangjiang city, the fast-charging stations deployment based on the proposed optimal model is more economical.



a) Cost comparison of different optimization planning methods



b) Convergence comparison of different optimization planning methods

Fig. 5. Cost and convergence comparison of different optimization planning methods

4.4 *Comparison under different time headways*

Compared to the transit operation in big cities, the time headway for most bus routes in Yangjiang City is relatively long. The further impact of different time headway on the result of the model is examined and analyzed. According to the bus operation schedule in Yangjiang City, the time headway is modified for bus routes with other model parameters fixed, and the results are shown in Figs. 6 and 7. The minimum fleet size of each bus route is given by Eq. (10). Three groups of time headways, namely, 20 minutes (Scenario 1), 15 minutes (Scenario 2) and 10 minutes (Scenario 3) are considered. It can be seen that with the decrease of time headway, the need for fast-charging spots, charging times of e-buses, the number of e-buses in service and charging load are all increased in the public transport network. The result is logical as the reduction in the time headway leads to an increase in the number of journeys and charging times.

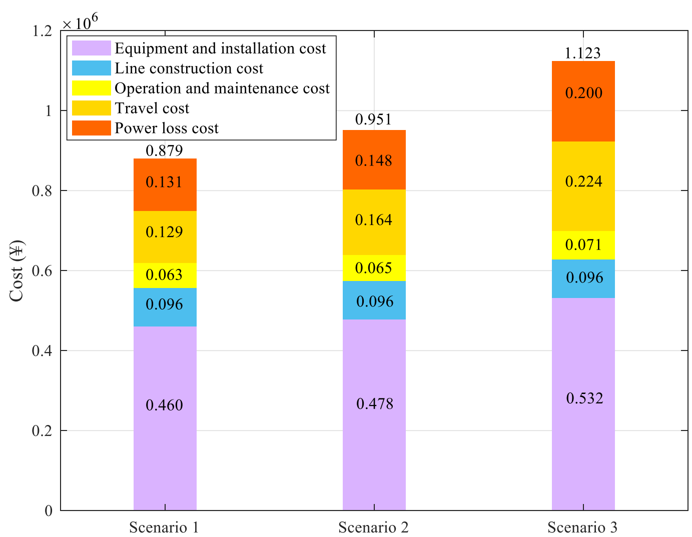
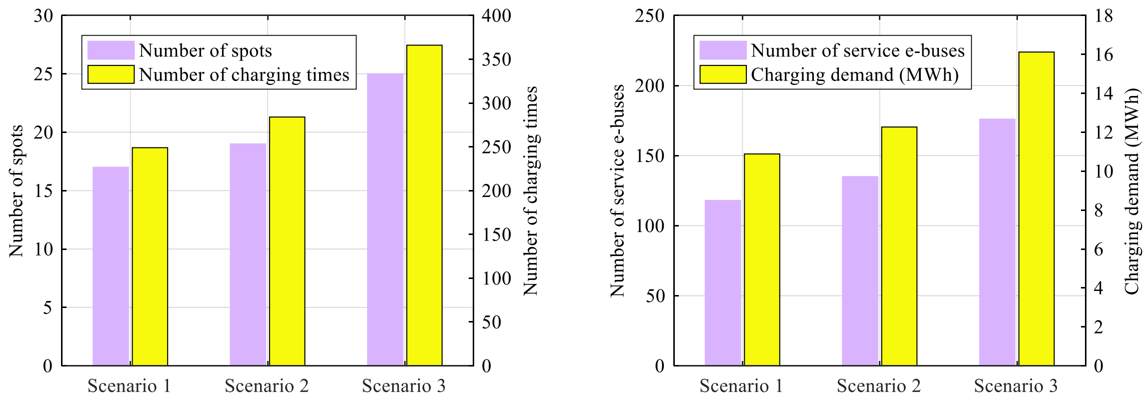


Fig. 6. Cost comparison under different time headways



a) Number of spots and charging times

b) Number of service e-buses and charging demand (MWh)

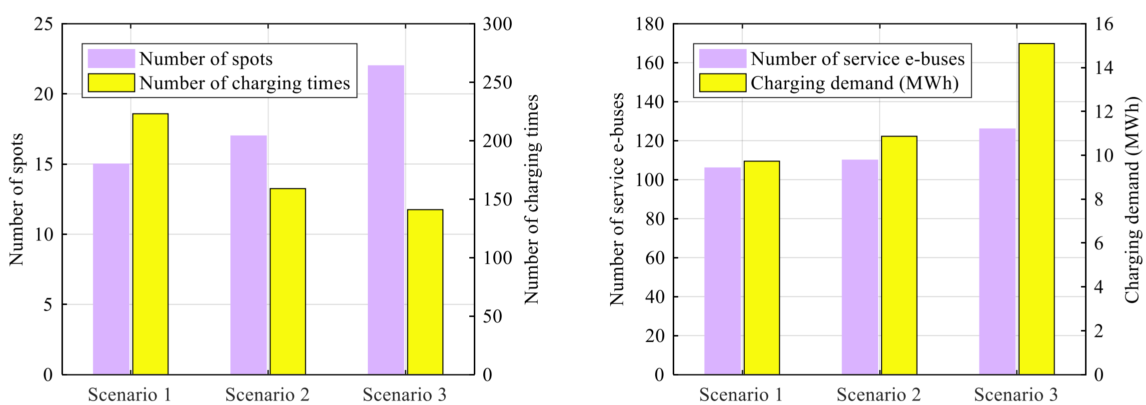
Fig. 7. Deployment comparison under different time headways

4.5 *Comparison under different battery size and charging power*

In addition, we also studied the impact of different types of e-buses on the proposed model. For simplicity, only the difference of battery capacity is considered. The e-bus models used are Yutong bus E6 (Scenario 1), E8 (Scenario 2) and E10 (Scenario 3), with battery parameter values illustrated in Table 5 [37]. Fig. 8 shows the comparison of charging details for different capacities of buses. It is assumed that when e-buses have enough power, they can operate longer and perform more tasks, and they can even meet the needs of a day's circular operation for a bus route with no need to be recharged. However, as seen from Fig. 8, the number of charging times decrease when the battery capacity of the buses is increased, while the number of fast-charging spots, service e-buses and charging demands increase. This is due to the increase in the battery capacity would lead to the required charging time increases. When a battery of e-bus is not fully charged, new e-buses are coming, resulting in an increase in the number of e-buses to be charged per unit of time. As a result, the number of fast-charging facilities, operating e-buses and charging demand are also increased. Furthermore, in order to investigate the influence of charging power, three groups of fast-charging facilities were set for comparison, namely 120 kW (Scenario 1), 150 kW (Scenario 2) and 180 kW (Scenario 3) of Star Charge brand [38], as shown in Fig. 9. The minimum fleet size for each bus route should satisfy Eq. (10). Fig. 9 shows that with the increase of charging power, there is a reduction in the number of fast-charging spots, charging times and operating e-buses. This is because as the charging power increases, less charging time is required for e-buses and more power is obtained per unit of time.

Table 5 Values of the battery sizes

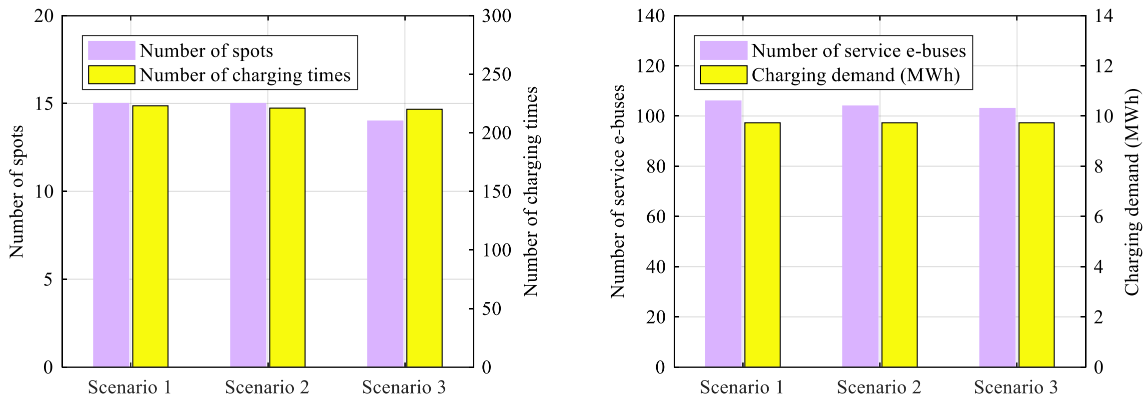
E-bus type	Battery capacity (kWh)
E6	85.85
E8	122.93
E10	202.93



a) Number of spots and charging times

b) Number of service e-buses and charging demand (MWh)

Fig. 8. Deployment comparison under different battery size



a) Number of spots and charging times b) Number of service e-buses and charging demand (kWh)

Fig. 9. Deployment comparison under different charging power

4.6 *Policy and business model implications*

The main stakeholders in electric bus public transportation include the central and local governments, electric bus manufacturers, users/bus companies, and providers of charging infrastructure. A number of issues in the electric bus industry has to be considered, such as policy implementation, technology innovation, business model and the whole supply chain.

Recently, new policies focused more on the construction, operation, and business models of charging facilities. For example, in China, there is the incentive policies on EV charging facility construction during the 13th five-year-plan [39]. In addition, new energy generation and energy storage technologies were considered to be an important part of the EV industry's strategy in 2016 [40]. A number of policies continue to support the construction and operation of charging facilities, especially those intended for public transportation systems.

With the integration of mobile energy storage into the power system and the build-up of charging infrastructure, there will be shifts in the value chain, the revenue model, and the value proposition. It is foreseen that a holistic approach will be used to explain how value is created [41].

The bus remains the most suitable solution from an economic, environmental, and social point of view regarding the balanced and sustainable urban development [42]. Urban public transportation is a multicriteria decision-making (MCDM) problem. For example, Gao et al. studied battery capacity and recharging [43] and Lai et al. proposed a financial model for lithium-ion storage [44]. A business model should be developed to identify appropriate specific evaluation criteria for electric buses transportation under clean technology and to select the transportation structures and elements such as charging station and batteries to maximize the contribution to sustainability and profit. Many methods could be considered such as computational intelligent methods for example deep neural network [45], genetic algorithm and particle swarm optimization. In summary, the present proposed method and studied system could be used as an example to further carry out sensitivity analysis and identify more parameters to develop business model and energy policy.

5. Conclusions

In this paper, the problem of deploying fast-charging stations at established bus terminus for e-buses is studied to ensure that buses on each bus route satisfies the energy demand. The purpose of this work is to identify optimal fast-charging stations at selected bus terminus to minimize the total cost of the transit system for deploying fast-charging stations. This paper proposes a planning model for locating and sizing the e-bus fast-charging stations, based on the consideration of both the bus operation network and distribution network. The Affinity Propagation clustering algorithm is used to cluster the bus terminuses, and then the Binary Particle Swarm Optimization algorithm is used to find the optimal solution of the deployed fast-charging station. The case study based on a real-world bus network is provided to demonstrate the effectiveness of the model. The objective is to reduce equipment redundancy in the station and excessive costs caused by excess charging stations. The decrease of the time headway will lead to the increase of fleet size and charging demand, thus increasing the total cost of fast-charging stations.

In future, the optimization model will be extended to different bus operation networks by customizing model data to assist the deployment of fast-charging stations in the electrification of bus networks in practice.

Acknowledgments

This work is sponsored in part by the China Southern Power Grid: Research on deployment of e-buses charging stations in Yangjiang City considering transportation network [Project Number GDKJ031700KK52180001]; Department of Finance and Education of Guangdong Province 2016 [202]: Key Discipline Construction Program, China; the Education Department of Guangdong Province: New and Integrated Energy System Theory and Technology Research Group [Project Number 2016KCXTD022]; Brunel University London BRIEF Funding, UK.

References

[1] C. S. Lai, L. L. Lai, Q. H. Lai. Smart grids and big data analytics for smart cities. Springer, October 2020. DOI https://doi.org/10.1007/978-3-030-52155-4

[2] Y. Wen, B. Cai, X. Yang, et al. Quantitative analysis of China's low-carbon energy transition. International Journal of Electrical Power and Energy Systems, 2020;119:105854.

[3] A. Lajunen, T. Lipman. Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. Energy, 2016;106:329–42.

[4] G. Correa, P. M. Muñoz, C. R. Rodriguez. A comparative energy and environmental analysis of a diesel, hybrid, hydrogen and electric urban bus. Energy, 2019;187:115906.

[5] M. Rupp, N. Handschuh, C. Rieke, et al. Contribution of country-specific electricity mix and charging time to environmental impact of battery electric vehicles: A case study of electric buses in Germany. Applied Energy, 2019;237:618–34.

[6] B. Zhou, Y. Wu, B. Zhou, et al. Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions. Energy, 2016;96:603–13.

[7] A. Nikoobakhta, J. Aghaei, T. Niknam, et al. Electric vehicle mobility and optimal grid reconfiguration as flexibility tools in wind integrated power systems. International Journal of Electrical Power and Energy Systems, 2019;110:83–94.

[8] N. B. G. Brinkel, M. K. Gerritsma, T. A. AlSkaif, et al. Impact of rapid PV fluctuations on power quality in the low-voltage grid and mitigation strategies using electric vehicles. International Journal of Electrical Power and Energy Systems, 2020;118:105741.

[9] M. Raoofat, M. Saad, S. Lefebvre, et al. Wind power smoothing using demand response of electric vehicles. International Journal of Electrical Power and Energy Systems, 2018;99:164–74.

[10] S. M. S. Hussain, M. A. Aftab, I. Ali, et al. IEC 61850 based energy management system using plug-in electric vehicles and distributed generators during emergencies. International Journal of Electrical Power and Energy Systems, 2020;119:105873.

[11] T. Capuder, D. Miloš Sprčić, D. Zoričić, et al. Review of challenges and assessment of electric vehicles integration policy goals: Integrated risk analysis approach. International Journal of Electrical Power and Energy Systems, 2020;119:105894.

[12] Z. Ji, X. Huang. Plug-in electric vehicle charging infrastructure deployment of China towards 2020: Policies, methodologies, and challenges. Renewable and Sustainable Energy Reviews, 2018;90:710–27.

[13] J. Yang, F. Wu, J. Yan, et al. Charging demand analysis framework for electric vehicles considering the bounded rationality behavior of users. International Journal of Electrical Power and Energy Systems, 2020;119:105952.

[14] S. Hosseini, MD. Sarder. Development of a Bayesian network model for optimal site selection of electric vehicle charging station. International Journal of Electrical Power and Energy Systems, 2019;105:110–22.

[15] C. Wang, R. Dunn, F. Robinson, et al. Active–reactive power approaches for optimal placement of charge stations in power systems. International Journal of Electrical Power and Energy Systems, 2017;84:87–98.

[16] Y. A. Alhazmi, H. A. Mostafa, M. M.A. Salama. Optimal allocation for electric vehicle charging stations using Trip Success Ratio. International Journal of Electrical Power and Energy Systems, 2017;91:101–16.

[17] I. Morro-Mello, A. Padilha-Feltrin, J. D. Melo, et al. Fast charging stations placement methodology for electric taxis in urban zones. Energy, 2019;188:116032.

[18] J. Du, F. Li, J. Li, et al. Evaluating the technological evolution of battery electric buses: China as a case. Energy, 2019;176: 309–19.

[19] National Development and Reform Commission. Implementation advice s on promoting consumption, expanding capacity, improving quality and accelerating the formation of a strong domestic market [EB/OL] [2020-02-28]. https://www.ndrc.gov.cn/xxgk/zcfb/tz/202003/ t20200313_1223046.html.

[20] Ministry of Industry and Information Technology. The equipment industry division I organized a symposium on the promotion of electric vehicles in the public sector 2020 [EB/OL]. http://www.miit.gov.cn/n1146290/n1146402/n1146440/c7824104/content.html.

[21] National Development and Reform Commission. Opinions on accelerating the establishment of a system of green production and consumption laws and policies 2020 [EB/OL]. https://www.ndrc.gov.cn/xxgk/zcfb/tz/202003/t20200317_1223470.html

[22] M. Mahmoud, R. Garnett, M. Ferguson, et al. Electric buses: A review of alternative powertrains. Renewable and Sustainable Energy Reviews, 2016;62:673–84.

[23] Z. Gao, Z. Lin, T. J. LaClair, et al. Battery capacity and recharging needs for electric buses in city transit service. Energy, 2017;122:588–600.

[24] Z. Bi, G. A. Keoleian, T. Ersal. Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization. Applied Energy, 2018;225: 1090–101.

[25] B. R. Ke, C. Y. Chung, Y. C. Chen. Minimizing the costs of constructing an all plug-in electric bus transportation system: A case study in Penghu. Applied Energy, 2016; 177:649–60.

[26] Y. He, Z. Song, Z. Liu. Fast-charging station deployment for battery electric bus systems considering electricity demand charges. Sustainable Cities and Society, 2019; 48:101530.

[27] X. Wang, C. Yuen, N. U. Hassan, et al. Electric vehicle charging station placement for urban public bus systems. IEEE Transactions on Intelligent Transportation Systems, 2017; 18(1):128–39.

[28] M. Xylia, S. Leduc, P. Patrizio, F. Kraxner, S. Silveira. Locating charging infrastructure for electric buses in Stockholm. Transp Res Part C Emerg Technol 2017;78:183–200.

[29] M. Rogge, E. van der Hurk, A. Larsen, and D. U. Sauer. Electric bus fleet size and mix problem with optimization of charging infrastructure. Appl Energy 2018;211:282–95.

[30] A. Lajunen. Lifecycle costs and charging requirements of electric buses with different charging methods. Journal of Cleaner Production 2018; 172:56–67.

[31] M. Rogge, S. Wollny, D. U. Sauer. Fast charging battery buses for the electrification of urban public transport—A feasibility study focusing on charging infrastructure and energy storage requirements. Energies, 2015; 8:4587–606.

[32] Bloomberg New Energy Finance. Electric Buses in Cities Driving Towards Cleaner Air and Lower CO2 Electric Buses in Cities. 2018.

[33] C. S. Lai, Y. Jia, M. D. McCulloch, et al. Daily clearness index profiles cluster analysis for photovoltaic system. IEEE Transactions on Industrial Informatics, 2017, 13(5): 2322-2332.

[34] B. J. Frey, D. Dueck. Clustering by passing messages between data points. Science, 2007; 315:972–6.

[35] J. Kennedy, R. C. Eberhart. Discrete binary version of the particle swarm algorithm. In: IEEE International Conference on System, Man, and Cybernetics. Computational Cybernetics and Simulation; 1997 October 12-15 volume 5 4104-8; Orlando, USA; 1997.

[36] M. Gómez, A. López, F. Jurado. Optimal placement and sizing from standpoint of the investor of photovoltaics grid-connected systems using binary particle swarm optimization. Applied Energy, 2010; 87:1911–1918.

[37] Yutong Bus. Yutong bus official website - Yutong is a leading road bus, bus, tourism bus, enterprise commuter bus, school bus and other large modern manufacturing enterprises. https://www.yutong.com/ (Accessed on 8 April 2020)

[38] Star Charge. Star Charge - faster and smarter - the country's leading car charging pile operator. http://www.starcharge.com/ (Accessed on 8 April 2020)

[39] Ministry of Science and Technology of the People's Republic of China. Notice on incentive policies for charging Infrastructure of new energy Vehicles during the 13th Five-Year Plan period and strengthening promotion and application of New energy Vehicles. http://www.most.gov.cn/tztg/201601/t20160120_123772.htm (Accessed on 12 November 2020)

[40] "Internet + Energy" Strategy, http://www.gov.cn/xinwen/2015-07/04/content_2890205.htm (Accessed on 12 November 2020)

[41] C. Zot, R.H. Amit, L. Massa. The business model: Recent developments and future research. Journal of Management, 2011, htp://dx.doi.org/10.1177/0149206311406265

[42] C. S. Lai, Y. Jia, Z. Dong, D. Wang, Y. Tao, Q.H. Lai, R. T. K. Wong, A.F. Zobaa, R. Wu and L.L. Lai. A review of technical standards for smart cities. Clean Technologies, MDPI, 2 (3), 2020, 290-310.

[43] Z. Gao, Z. Lin, T. J. LaClair, C. Liu, J. M. Li, A. K. Birky, J. Ward. Battery capacity and recharging needs for electric buses in city transit service. Energy, 2017, 122, 588–600.

[44] C. S. Lai, G. Locatelli, A. Pimm, Y. Tao, X. Li, L. L. Lai. A financial model for lithium-ion storage in a photovoltaic and biogas energy system. Applied Energy, vol 251, 1 October 2019, 113179.

[45] C. S. Lai, Z. Mo, T. Wang, H. Yuan, W. W. Y. Ng, L. L. Lai. Load forecasting based on deep neural network and historical data augmentation. IET Generation, Transmission & Distribution, 2020. DOI: 10.1049/iet-gtd.2020.0842.