RESEARCH ARTICLE

En-Route Charging Strategy for Wirelessly Charged Electric Bus Considering Time-of-Use Price

WEILIANG ZENG , PANLONG LIU, CHAO YANG , WEIJUN SUN, YONGHUI HUANG, AND YU HAN

Guangdong Engineering Center of Auto-detection Technology for Intelligent Manufacturing, School of Automation, Guangdong University of Technology, Guangzhou 510006, China

Corresponding author: Yonghui Huang (gracehuang02@163.com)

ABSTRACT To mitigate the range anxiety problem of electric bus system, wireless power transfer is regarded as one of the emerging technologies for long-term range extension. Previous studies have discussed the optimization problem of the power track deployment. However, the en-route charging strategy also significantly influences the operation cost besides the power track, which is yet to be investigated sufficiently. To fill this gap, a new wireless charging model for optimizing the energy cost is proposed. In particular, the cost of battery and the time-of-use electricity price are taken into account. Firstly, a microscopic power consumption model considering passenger flows and automobile dynamics is developed to estimate the charging cost. Then, a relaxation approach based on penalty function and grey wolf optimization (GWO) algorithm is developed to solve the non-deterministic polynomial-hard (NP-hard) problem with complex multidimensional variables and multiple inequality constraints. And the performance of the proposed charging strategy is verified in a real-world bus line via numerical simulation. A sensitivity analysis is conducted to quantify the marginal impact of the unit cost of battery capacity on the total energy cost. Finally, the computational performance of the proposed algorithm (GWO) is validated by comparing other outstanding methods such as genetic algorithm (GA), particle swarm optimization (PSO) and CPLEX solvers.

I. INTRODUCTION

The World Energy Outlook reported that the number of global electric vehicle exceeded 10 million in 2020, which increased 43% from 2019 [1], indicating that the market of electric vehicle will be growing rapidly in the future. However, the issue of range anxiety still hampers the promotion of electric bus (EB) system [2], [3], [4], [5]. Electric vehicles (EVs) with wireless power transfer (WPT) technology have been introduced to solve this problem [6], [7]. However, the cost of operating a wireless charged electric bus (WCEB) line is still

expensive. The cost mainly includes power track deployment cost, battery cost and charging cost [8]. Previous studies have focused on optimizing the cost of the power track deployment [9], [10], [11], [12], but the optimization of the battery cost and charging cost during operation is yet to be investigated sufficiently.

The total cost of battery and charging are defined as the energy cost in this study, which are mainly related to the battery capacity, the electricity price and the charging strategy. Due to the limitation of battery capacity, the range anxiety problem has plagued many electric vehicle users [13], [14], [15]. Several techniques have proposed to mitigate this problem, e.g., brake regeneration [16], [17], power

TABLE 1. Summary of the selected literature on wirelessly charged EV modeling.

Literature	Object	Objective function	Constraints	Methodology
[38]	Bus	The cost of the battery, the power tracks and the total number of EB.	DWC facility and energy consumption	Bi-level mixed integer nonlinear programming (MINP)
[7]	Bus	The cost of battery and power tracks	Energy consumption and range	Continuous Meta-heuristic
[12]	Bus	The cost of battery, inverter and power tracks	Energy consumption and range	Segmentized mixed integer programming (MIP) Meta-heuristic
[8]	Bus	The logistics cost	Energy consumption and range	Segmentized MIP
[11]	Bus	The total fixed cost and the variable cost of the power tracks and battery	Energy consumption and range	Continuous Meta-heuristic
[9]	Bus	The cost of the transmitters and battery.	Energy consumption and range	Continuous MINP Meta-heuristic
[48]	General vehicles	The total social cost	Range and budget	Bi-level MIP
[37]	General vehicles	The system travel time and energy consumption	Range and budget	Bi-level MINP
[54]	Bus	The cost of power tracks	Range and budget	Bi-level MIP

management [18], and eco-driving in mixed connected traffic [19], [20], [21]. However, the limited coverage of charging stations and the charging waiting time remain the primary barriers to long-distance driving. For EBs, equipping with large-capacity battery might be a possible solution for the range anxiety problem, but it is not economical and environmentally friendly [22]. The larger the capacity is, the longer charging time will be, which might result in higher operation cost [23]. Compared with the traditional plug-in charging technology, WPT allows EBs to be connected to the grid for charging en-route. Besides, it is possible to decentralize charging times for better adaption to the profile of the time-of-use (TOU) electricity price.

TOU price is a typical price-based demand response mechanism [24], [25] enabling to save energy consumption from the perspective of the supply-demand relationship [26], [27], [28]. For example, in [26], the charging/discharging scheduling for an EV parking lot was planned based on TOU price, which shown that the peak electricity consumption could reduce by about 20%. In [28], the authors modeled the day-ahead scheduling of the power system as a mixed integer linear programming problem to minimize the peak electricity consumption. The charging strategies based on TOU price for plug-in charging EVs were discussed in [29], [30], [31], and [32]. In [29], the authors proposed a TOU price incentive-based charging navigation strategy for EVs, and in [30], the charging station queuing factor was added based on [29]. In [31] and [32], the optimal charging strategy for EVs was proposed, which minimized the charging cost considering the transformer power margin and parking fee with the TOU price.

Compared with the plug-in pattern, the WCEB enables frequent and multi-period charging, potentially enabling

to adapt to the TOU pricing mechanism [11]. Wirelessly charged EVs using WPT technology has also been proven to be better in reducing battery capacity specifications and mitigating the range anxiety [33]. Though the cost of deploying WPT may be higher than that of the wired charging device [34], it is acceptable to the future transit system because it helps to mitigate the range anxiety, reduce the weight of battery, and optimize the long-term operation cost [35]. In [33], the authors developed an integrated life cycle assessment model to evaluate the cost of an all-EB system with plug-in or wireless charging technology. Korea Advanced Institute of Science and Technology (KASIT) reported that the WCEB was possible to achieve the power efficiency of 83% at an output power of 60 kWh [12]. Similarly, the PRIMOVE system for WCEB made by Bombardier enabled a charging power of up to 200kWh with a conversion efficiency of more than 90% [36]. They all found that the WCEB system is more economically competitive than the plug-in charging EB system.

The total cost of WCEB system is mainly contributed by the power track, the vehicle battery and the charging strategy [8]. Previous research has focused on the optimization of the cost of power track [7], [9], [12], [37] and [38], but the battery capacity and charging strategy are yet to be studied sufficiently. A summary of selected works on optimizing the charging cost of wirelessly charged EVs is given in Table 1. In [7], the cost of battery and power tracks with the constraint of energy consumption and the driving range were optimized by using the continuous Meta-heuristic approach. In [38], a bi-level mixed integer nonlinear programming (MINP) was proposed to optimize the total cost including the battery, the power tracks and the EBs. A similar approach was implemented to minimize the cost of the transmitters and battery

was proposed in [9]. In [11], the authors quantified the benefits of three charging methods, i.e., static wireless charging, dynamic wireless charging (DWC) and quasi-dynamic wireless charging. The optimal charging strategy for various market conditions and initial investment cost was discussed in [12]. They concluded that the dynamic charging strategy is beneficial to prolong the life-span of battery. Considering the operation cost, a comprehensive model for WPT location distribution was developed, which incorporated the operational-level information such as the number of trips for each line [54]. However, how the TOU electric price and the passenger flow influence on the charging schedule was not discussed.

In summary, previous studies have shed light on the charging strategy for EVs and the deployment of wirelessly charged device. However, limited studies investigate the optimization of the en-route charging schedule for the WCEB system. To fill this gap, this study aims to optimize the en-route charging schedule for WCEB. The main contributions of this study are listed as follows.

(1) A model jointly optimizing the charging cost and battery cost for a WCEB line is proposed. Unlike previous studies focusing on the power track location distribution, this study aims to optimize the charging start time, the charging end time and the battery capacity from the operational perspective rather than how to optimize the cost for the power track deployment. The proposed model also enables to adapt to the TOU based electricity price.

(2) A relaxation approach based on penalty function is applied to transform the wireless charging problem that belongs to the generally complex constrained optimization problem into an unconstrained problem. Accordingly, the GWO algorithm is applied to solved the constrained optimization problem by finding the optimal solution of the unconstrained problem iteratively.

The rest of this paper is organized as follows. Section 2 presents the methodology for constructing the en-route wireless charging strategy and the energy consumption model. Section 3 conducts a case study where the proposed framework is evaluated in both quantitative and sensitivity studies. Section 4 draws conclusion of this study and describes future extensions.

II. METHODOLOGY
A. NOTATION
Notations used in this study are given in Table 2.

The charging mode for the WCEB system is shown in Figure 1. Assumed that the operation route for an EB contains η power tracks and an EB runs ϖ cycles in one day, the number of passing power tracks can be regarded as $n = \eta * \varpi$. Accordingly, the decision variables for the charging strategy can be represented by the sequence of charging start time (t_s) and the charging end time (t_f), i.e., $T_n = \left\{ \left(t_s^1, t_f^1\right), \ldots \left(t_s^i, t_f^i\right) \ldots, \left(t_s^n, t_f^n\right) \right\}$, which consists of n starting charging moments and ending charging moments

TABLE 2. Notation definition.

| Notation	Definition
W_z	The total energy cost
W_e	The battery cost
W_c	The charging cost per day
d	The number of days
$y(t)$	The charging price at time t
$E(t)$	The remaining battery power at time t
E_{min}	The minimum remaining power
t_s^i	The time to start charging in the ith power track
t_f^i	The time to end charging in the ith power track
E_0	The battery capacity
σ	The conversion factor of the charging power
$p_x(t)$	The power consumption at time t
p_c	The charging power
u_e	The unit battery cost
t_a^i	The time of arriving at the ith power track
t_l^i	The time of leaving the ith power track
t_d	The driving time
t_ε	The stopping time
t_{ave}	The average boarding time
k_{on}^j	The number of passengers getting on at the jth station
k_{off}^j	The number of passengers getting off at the jth station
$p_d(t)$	The effective power of the generator at time t
β	The conversion factor of the engine power
p_u	The additional energy consumption
$m(t)$	The total weight
m_b	The weight of the bus
m_{ave}	The average weight per passenger
$\varepsilon(t)$	The number of passengers on the bus
ε_{max}	The maximum passenger capacity
g	The gravitational acceleration
θ	The road inclination
$a(t)$	The acceleration at time t
$v(t)$	The vehicle speed at time t
A_f	The cross-sectional area of the bus
ρ_{air}	The air mass density
C_D	The air resistance coefficient
C_r, c_1, c_2	The rolling resistance parameters
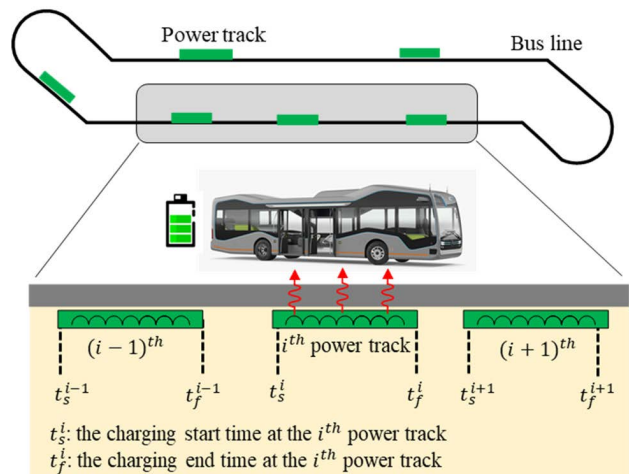
FIGURE 1. Illustration of the charging mode for the WCEB system.

for a one-day operation cycle. t_s^i and t_f^i are the charging start time and the charging end time for the ith power track,

respectively. Thus, the optimization of the total energy cost is mainly dependent on the selection of the battery capacity E_0, the charging start time t_s^i and the charging end time t_f^i.

B. MODEL CONSTRUCTION

1) CHARGING STRATEGY MODELLING

The energy cost of WCEB operation is mainly from the battery cost and the electricity cost. Thus, we propose a charging strategy considering the battery capacity and the TOU electricity price as shown in Eq.(1).

$$\text{Min } W_z = W_e + dW_c \tag{1}$$

$$\text{s.t. } E\left(t_s^i\right) = E\left(t_f^{i-1}\right) - \int_{t_f^{i-1}}^{t_s^i} p_x\left(t\right)dt \geq E_{min}, \quad \forall i \tag{2}$$

$$E\left(t_f^i\right) = E\left(t_s^i\right) + \int_{t_s^i}^{t_f^i} \left(\sigma p_c - p_x\left(t\right)\right)dt \leq E_o, \quad \forall i \tag{3}$$

$$t_a^i \leq t_s^i \leq t_f^i \leq t_l^i, \quad \forall i \tag{4}$$

$$t_f^{i-1} \leq t_l^{i-1} < t_a^i, \quad \forall i \tag{5}$$

$$E\left(t_0\right) = E_0, \quad t_0 = 0 \tag{6}$$

$$E\left(t_f^n\right) = E_0 \tag{7}$$

where W_e is the battery cost, W_c is the charging cost per day, and d is the number of the operation days.

$$W_e = u_e E_0 \tag{8}$$

where u_e is the unit battery cost, referring to the cost of per kWh capacity [49].

$$W_c = \sum_{i=1}^{n} \int_{t_s^i}^{t_f^i} y\left(t\right) p_c dt \tag{9}$$

where $y\left(t\right)$ is the charging price at time t and p_c is the charging power.

The remaining battery power during the whole operation period cannot exceed the rated battery capacity E_o, nor can it be lower than the minimum remaining power, which can be presented by the following constraint.

$$E_{min} \leq E\left(t\right) \leq E_o \tag{10}$$

where $E\left(t\right)$ is the remaining battery power at each moment during operation, and E_{min} is the minimum remaining power.

In Eq.(2) and Eq. (3), $E\left(t_s^i\right)$ is the remaining battery power at the start moment of the ith charging and $E\left(t_f^i\right)$ is the remaining battery power at the end moment of the ith charging. σ is the conversion factor of the charging power. p_x is the consumed power estimated by the energy consumption model. Eq. (2) is the battery remaining power at the beginning of any charging moment, which must be greater than the lower bound value (E_{min}). Eq. (3) is the battery remaining power at the end of any charging moment, which must be less than the capacity of the battery (E_o). Since the power consumption must be less than the charging power, the energy consumption constraints need to satisfy Eq. (2) and Eq. (3).

As shown in Eq. (4) and Eq. (5), the charging start time and the charging end time are constrained by the power track distribution. The t_a^i and t_l^i are the time when the EB arrives at and leaves the ith power track, respectively. t_d^i is the driving time from the $(i-1)^{th}$ power track to the ith power track. t_ε^i is the total stopping time at bus station.

$$t_a^i = t_l^{i-1} + t_d + t_\varepsilon \tag{11}$$

$$t_l^i = t_a^i + t_d \tag{12}$$

The stopping time at a bus station depends on the number of passengers getting on and off the bus. Thus, the stopping time (t_ε) can be represented by Eq.(13).

$$t_\varepsilon = \sum_{j=q} t_\varepsilon^j \tag{13}$$

$$t_\varepsilon^j = t_{ave} max\left\{\varepsilon_{on}^j, \varepsilon_{off}^j\right\}, \quad j = 1, 2, \ldots \varphi \tag{14}$$

where q refers to the station number between the $(i-1)^{th}$ and i^{th} power track. ε_{on}^j and ε_{off}^j are the number of passengers getting on and off at the jth bus station, φ is the number of bus station passed.

Eq. (6) and Eq.(7) are the boundary conditions. Eq.(6) means that the initial battery power is set to the battery capacity E_0. In Eq.(7), the remaining power of the WCEB is set to a fully charged state at the end of the one-day cycle.

2) ENERGY CONSUMPTION MODEL

To facilitate the optimization of the TOU based charging strategy, a dynamic time-dependent energy consumption model is necessary to estimate the power consumption [39]. Considering that the power consumption $p_x\left(t\right)$ in Eq.(2) consists of the engine power ($p_d\left(t\right)$) and other energy consumption (p_u), $p_x\left(t\right)$ can be presented by Eq.(15).

$$p_x\left(t\right) = \frac{p_d\left(t\right)}{\beta} + p_u \tag{15}$$

where β is the conversion factor of the engine power.

In Eq.(15), the effective power ($p_d\left(t\right)$) of the generator can be estimated by the sum of the rolling resistance power, the slope resistance power, the air resistance power and the acceleration resistance power [40]. Thus, the effective power can be formulated by Eq.(16).

$$p_d\left(t\right) = \left(\delta m \cdot a\left(t\right) + mgr\cos\left(\theta\right) + \frac{1}{2}\rho_{air}A_f C_D v^2\left(t\right)\right. $$
$$\left. + mg\sin\left(\theta\right)\right)v\left(t\right) \tag{16}$$

where m is the weight of the bus, g is the gravitational acceleration, θ is the inclination of the road, $a\left(t\right)$ is the acceleration of the EB at time t, $v\left(t\right)$ is the vehicle speed at time t, A_f is the area of the vehicle subject to the air resistance, ρ_{air} is the air mass density, C_D is the air resistance coefficient of the bus, and r is the rolling resistance coefficient given by Eq.(17).

$$r = \frac{C_r}{1000}\left(c_1 \cdot v\left(t\right) + c_2\right) \tag{17}$$

where C_r, c_1, c_2 are the rolling resistance parameters depending on the road type, the road condition and the vehicle tire, respectively.

Since the number of passengers onboard is an important factor affecting the total weight, it is necessary to take it into account in the energy consumption model. The total weight of the bus and the passengers onboard can be represented by Eq.(18).

$$m(t) = m_b + m_{ave}\varepsilon(t) \tag{18}$$

$$\varepsilon(t) = \varepsilon\left(t^j\right) + \varepsilon_{on}^j - \varepsilon_{off}^j, \quad t^j < t \le t^{j+1}, \tag{19}$$

$$0 \le \varepsilon(t) \le \varepsilon_{max} \tag{20}$$

where $\varepsilon\left(t^j\right)$ is the number of the onboard passengers when the bus arrives at the jth bus station, ε_{on}^j and ε_{off}^j are the number of passengers getting on and off at the jth station, respectively.

C. MODEL SOLUTION

Noticed that the optimization problem for the charging strategy (Eq.(1)-Eq.(7)) is an NP-hard problem with complex multidimensional variables and multiple inequality constraints, a relaxation approach based on the penalty function is developed to solve the constrained optimization problem and then the GWO algorithm is applied to iteratively approximate the solution.

1) RELAXATION OF THE CONSTRAINED PROBLEM

When solving constrained optimization problems, it is necessary to eliminate the constraints [40]. The basic idea of the relaxation approach based on penalty function is to transform the complex constrained optimization problem into an unconstrained problem, and finally approximate the solution by searching for the optimal solution of the unconstrained problem iteratively [41].

The relaxation approach based on penalty function can be divided into two categories: the outer-point approach and the inner-point approach. The outer point approach is suitable for constructing penalty terms of equality constraints, while the inner-point approach is suitable for constructing penalty terms of inequality constraints [42]. Since the optimization problem has both inequality constraints and equality constraints, the optimization model in this study can be represented by Eq.(21)-Eq.(23) as follows.

$$\min W_z(t, E_0) \tag{21}$$

$$\text{s.t.} \quad h_x(t, E_0) = 0, \quad x = 1, 2, \dots, \partial \tag{22}$$

$$q_y(t, E_0) \ge 0, \quad y = 1, 2, \dots, \alpha \tag{23}$$

Eq.(22) corresponds to the equality constraints, i.e., Eq.(6) and Eq.(7). Eq.(22) corresponds to the inequality constraint, i.e., Eq.(2),Eq.(2),Eq.(3) and Eq.(4). Thus, the penalty term can be constructed by the outer-point approach for the equality constraint as $\sum_{x=1}^r [h_x(t, E_0)]^2$, and it can be constructed by the inner-point approach for the inequality constraint as $\sum_{y=1}^a \frac{1}{q_y(t,E_0)}$. After constructing the penalty function, the
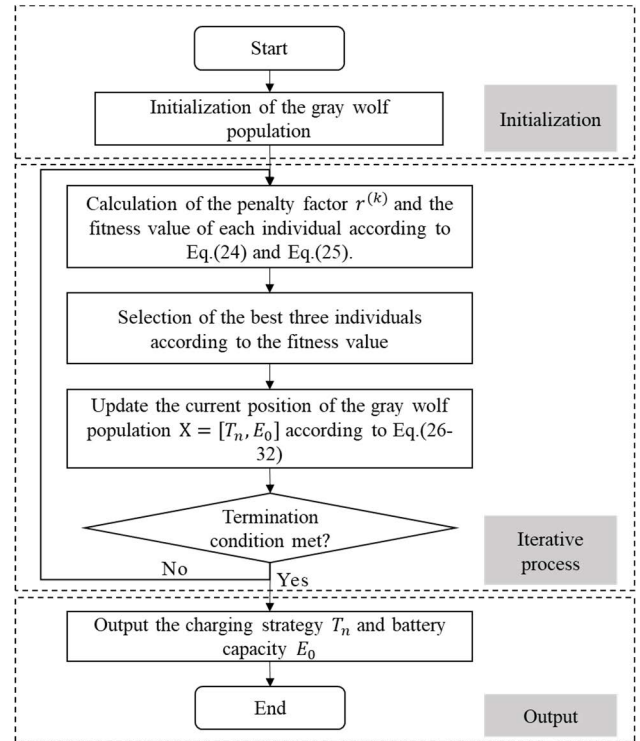

FIGURE 2. The flow chart of the GWO algorithm.

original problem can be transformed to an unconstrained minimization problem by Eq.(24).

$$\begin{aligned}
\text{Min } F&\left[T_n, r^{(\sigma(k))}, E_0\right] \\
&= W_z(T_n, E_0) + \frac{1}{\sqrt{r^{(\sigma(k))}}} \sum_{x=1}^r [h_x(t, E_0)]^2 \\
&\quad + r^{(\sigma(k))} \sum_{y=1}^a \frac{1}{q_y(t, E_0)}
\end{aligned} \tag{24}$$

where $r^{(\sigma(k))}$ is the penalty factor.

To improve the search efficiency, the penalty factor can be updated iteratively by Eq.(25).

$$r^{(\sigma(k))} = 10^{(1-\sigma(k))\frac{2k-1}{k}} \tag{25}$$

where $\sigma(k)$ is the ratio of feasible solution to unfeasible solution for the unconstrained problem in the kth iteration [51].

2) GREY WOLF OPTIMIZATION (GWO) ALGORITHM

GWO is a searching method inspired by the prey activity of grey wolves [43]. It has strong convergence performance on solving multi-peak and multi-dimensional NP-hard problems [44].

Figure 2 shows the calculation process of the GWO algorithm. First, it divides the wolves into four levels, i.e., λ, μ, δ and ϱ, according to the size of the fitness value. λ, μ and δ are the wolves in top three levels, while the ϱ is the remaining wolves. The wolf pack ϱ realizes the optimization process of the whole algorithm. The three high-level wolves λ, μ
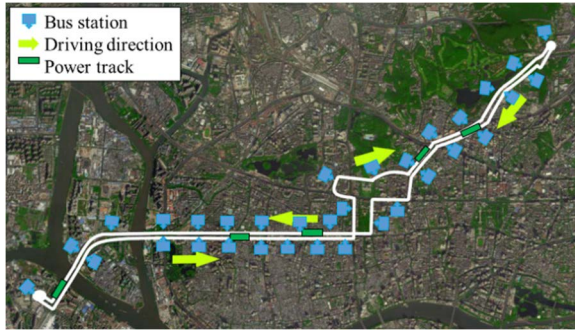
FIGURE 3. The bus line in the simulation study.

TABLE 3. The location of power track deployment.

POWER TRACK	Deployment location
Power track 1	6721-6889m
Power track 2	12330-12485m
Power track 3	19902-20120m
Power track 4	27603-27801m
Power track 5	32770-32891m

TABLE 4. The local TOU charging price.

Time period division	Tariff (RMB/(kWh))	Time period
10:00-15:00,18:00-21:00	1.322	Peak
7:00-10:00,15:00-18:00, 21:00-23:00	0.832	Flat
23:00-7:00	0.369	Valley

TABLE 5. Parameter setting for the energy consumption model.

Parameters	Definition	Data source
σ	0.9	[37]
p_c	200kW	[37]
C_r	1.75	[48]
c_1	0.03	[48]
c_2	4.5	[48]
$\rho_{air}(kg/m^3)$	1.2256	[48]
C_D	0.9	[48]
$A_f(m^2)$	2.55×3.63	[48]
β	0.85	[48]
$m_b(kg)$	13500	Yutong Bus Company
ε_{max}	50	Yutong Bus Company
$m_{ave}(kg)$	50	Yutong Bus Company
t_{ave}	2s	Yutong Bus Company
E_{min}	6kWh	Yutong Bus Company
$p_u(kW)$	3	Yutong Bus Company
u_e	1500 RMB/kWh	[51]
$g(m/s^2)$	9.8	/

and δ are assumed to have the potential ability to obtain the location of the prey and jointly command the wolf pack ϱ. Then, the wolf pack ϱ feed back the information to the three high-level wolves who decide whether the information needs to be updated. When the number of the iterations reaches to the threshold value, the positions of λ, μ and δ, i.e., X_λ, X_μ and X_δ can be obtained. X_λ, X_μ and X_δ can be regarded as the top three candidate solutions to the optimization problem [43].

The objective function, i.e., Eq.(24), can be regarded as the fitness function in GWO algorithm. And the variables X_λ, X_μ and X_δ to be solved in GWO can be represented by Eq.(26).

$$X = [T_n, E_0] \qquad (26)$$

The specific formulation of the GWO algorithm can be expressed by the following equations.

$$\begin{cases} D_\lambda = |C_1 X_\lambda - X_\varrho| \\ D_\mu = |C_1 X_\mu - X_\varrho| \\ D_\delta = |C_1 X_\delta - X_\varrho| \end{cases} \qquad (27)$$

$$\begin{cases} X_1 = X_\lambda - B_3 D_\lambda \\ X_2 = X_\mu - B_3 D_\mu \\ X_3 = X_\delta - B_3 D_\delta \end{cases} \qquad (28)$$

$$X_\varrho(k+1) = \frac{X_1 + X_2 + X_3}{3} \qquad (29)$$

$$B = 2\psi(\tau_1 - 1) \qquad (30)$$

$$C = 2\tau_2 \qquad (31)$$

$$\psi(k) = 2\cos\left(\frac{k}{M}\pi\right) \qquad (32)$$

where D_λ, D_μ and D_δ are the direction vectors between the three high-level wolves λ, μ, δ and the wolf pack ϱ. X_1, X_2 and X_3 are the direction vector of the wolf pack ϱ towards λ, μ, and δ, respectively. Eq.(29) defines the final position of ϱ. C and B are the swing factor, which are determined by Eq.(30) and Eq.(31). τ_1 and τ_2 are the random numbers between 0 and 1. $\psi(k)$ is the convergence factor, which decreases as the iteration increases. k is the current number of iterations, and M is the maximum iteration number [44].

III. NUMERICAL ANALYSIS
A. EXPERIMENT SETTING
To demonstrate the performance of the proposed wireless charging strategy, a bus line in Guangzhou, China, is used to test the model in VISSIM. The simulation scenario and the traffic flow are generated according to the traffic data issued by Guangzhou Institute for Transportation and Development Policy [45]. As shown in Figure 3, the length of bus line is 32,960 meters and the bus service begins at 5.30 a.m. There are 5 wireless power tracks and 33 bus stops along the bus line. The bus runs 15 cycles in one day, thus the total number of charging opportunities (n) is 75. Accordingly, the total stopping times at bus stops (φ) is 495. Table 3 shows the location of the power track. According to [46], the local TOU price is given in Table 4.

According to the vehicle parameters provided by Yutong Bus Company, road surface coefficients and resistance
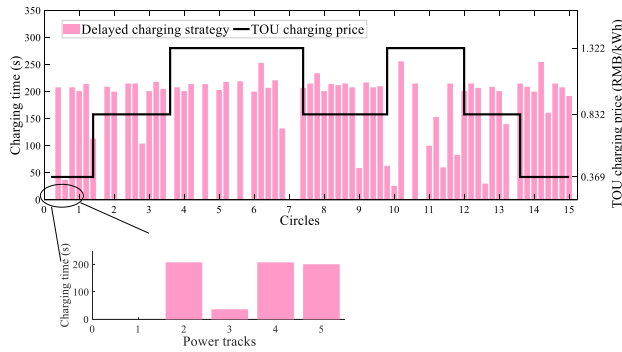
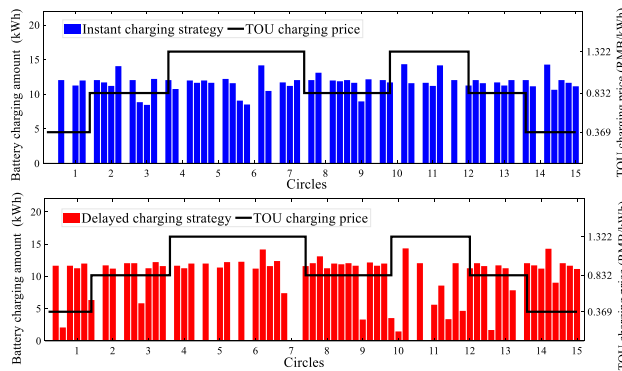**FIGURE 4.** Illustration of the delayed charging strategy.

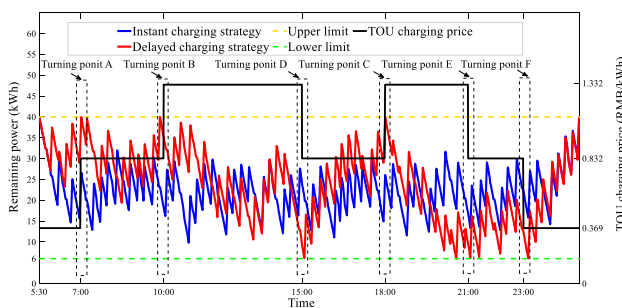**FIGURE 5.** Delayed charging strategy vs. instant charging strategy.

FIGURE 6. Comparison of the remaining power between the delayed charging and instant charging strategies.

constants provided by [47] and [36], the parameter setting of the energy consumption model is given in Table 5.

B. RESULTS

Model comparison and sensitivity analysis are given to demonstrate the model performance. The charging time and cost are used as the evaluation indicators. A sensitivity analysis is performed to investigate the influence of some key parameters on the model.

1) CASE STUDY

To facilitate the discussion, the proposed charging strategy T_n based on TOU price guidance in this paper is referred to the

TABLE 6. The battery charging amount of delayed and instant charging strategies.

TOU Price (RMB/kWh)	Delayed charging strategy	Instant charging strategy	Difference
0.369	141.61	118.49	+23.12
0.832	295.85	266.28	+29.57
1.322	205.02	257.71	−52.69
TOTAL	642.48	642.48	0

TABLE 7. The battery charging cost of delayed and instant charging strategies.

TOU Price (RMB/kWh)	Delayed charging strategy	Instant charging strategy	Difference
0.369	52.254	43.723	+8.531
0.832	246.147	221.545	+24.602
1.322	271.036	340.693	−69.657
Total	569.437	605.961	−36.524

delayed charging strategy, which enables to select a charging chance with relatively lower electricity price. With the above experiment setting, the optimized charging strategy T_n is shown in Figure 4. It demonstrates that the WCEB decides to charge at the current power track or defer charging until arriving at the next power track. The instant charging strategy is used as the benchmark for comparison, which means that when the remaining power of the battery falls below a certain level, the WCEB decides to charge at the current power track instantly.

As shown in Figure 5, the battery charging amount distribute relatively balanced in the whole operation circles with the instant charging strategy, while it is concentrated in the period of lower electricity price with the delayed charging strategy which is guided by the TOU electricity price. We also explore the energy consumption pattern of the two charging strategies.

According to the battery charging amount in Figure 5, we compare the curves of the remaining power in Figure 6. The turning points shows the time when the TOU price changes. The turning points A, B, and C on the curve of the delayed charging strategy indicate that when the charging price rises from the off-peak price to the peak price, the WCEB decides to reduce charging to save the energy cost unless the remaining power is lower than the threshold. In contrast, the turning points D, E, and F show that when TOU charging price switches from the peak price to the off-peak price, or from off-peak price to valley price, the WCEB starts to increase charging until the charging amount reaches to the battery capacity. However, the instant charging strategy can not guide to charge in off-peak price periods.

Tables 6 and Table 7 illustrate the energy cost of the two charging strategies. In the off-peak hours, i.e., 0.369 RMB/kWh, the delayed charging strategy guides to charge 141.61kWh, while the instant charging strategy guides to charge 118.49 kWh. It indicates that the bus can charge
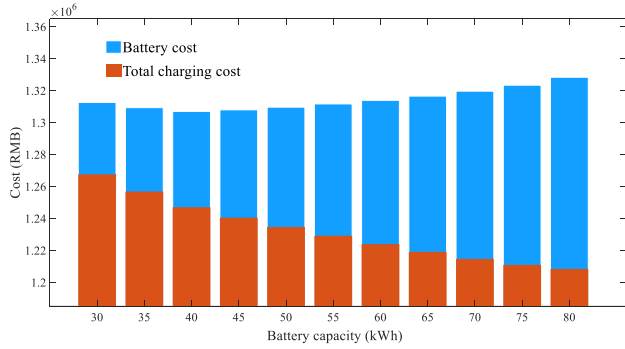
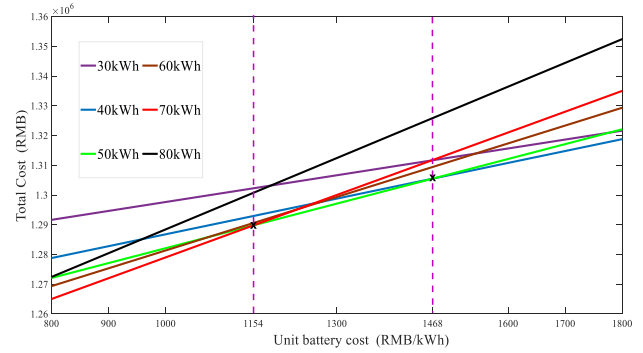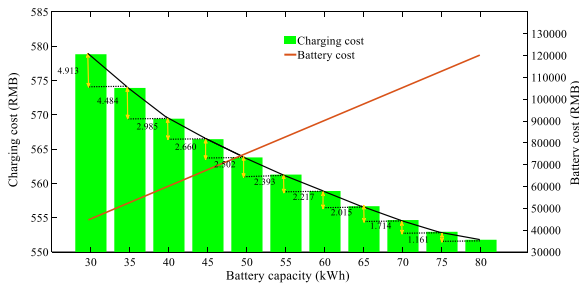**FIGURE 7.** The impact of battery capacity on cost.

FIGURE 8. Marginal effect of charging cost at different specifications of battery capacity.
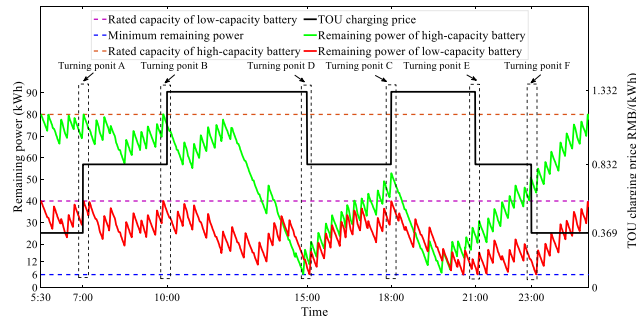

FIGURE 9. The remaining power of WCEB with the delayed charging strategy.

more amount of electricity with the delayed charging strategy when the TOU price is lower. In the peak hours, i.e., 1.322 RMB/kWh, the delayed charging strategy can guide to charge 205.02kWh, while the instant charging strategy guides to charge 257.71 kWh. It indicates that the bus can charge less amount of electricity with the delayed charging strategy when the TOU price is higher. According to the statistics in Table 7, the daily charging cost is 569.437 RMB by using the delayed charging strategy, while it is 605.961 RMB by using the instant charging strategy. It indicates that the delayed charge strategy enables to a daily savings of 36.524 RMB and a yearly savings of 13,331.26 RMB.

FIGURE 10. The impact of unit battery cost on the total cost.

TABLE 8. Computational performance of four solvers.

Solution	Objective Value	Computation Time(s)	Solution Gap(%)
GWO	569.437	3.237	0.047
GA	570.954	8.243	0.313
PSO	600.254	4.854	5.46
CPLEX	569.168	113.23	0

2) SENSITIVITY ANALYSIS

Because the unit battery cost varies widely in the market, it is vital to investigate the effect of battery capacity and unit battery cost on the energy cost [52]. The charging costs with various battery capacity specifications are tested by the delayed charge strategy as shown in Figure 7. It is found that as the battery capacity increases (indicating the battery cost increases), the charging cost gradually decreases. Since the unit battery cost is a constant value, the growth rate of the battery cost is also constant. When the battery capacity is larger than 40kWh, the decreasing rate of the charging cost is less than the increasing rate of the battery cost, which results in the minimum total cost.

Figure 8 illustrates the marginal diminishing effect of the daily charging cost. Though the battery with larger capacity can lengthen the driving time, the unit charging cost can not reduce in proportion because the high-capacity battery cost more. It means that the total cost will increase by using the battery with larger capacity.

Because the delayed charging strategy can adapt to the TOU electricity price, the charging behavior is often intermittent. That means the high-capacity batteries cannot be fully utilized. To illustrate this phenomenon, the delayed charging strategies with 40 kWh and 80 kWh battery tested to investigate the energy consumption for the high-capacity battery and low-capacity battery. As shown in Figure 9, when the charging price was rising from off-peak to peak, the high-capacity battery was not fully charged. In the same condition, the low-capacity battery can be fully charged. It means that the delayed charging strategy using low-capacity batteries can respond to TOU energy prices more efficiently, because the battery capacity can be fully utilized.
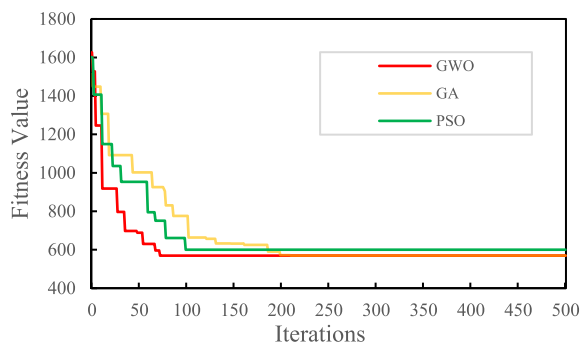
FIGURE 11. Convergence analysis for the three heuristic algorithms.

As shown in Figure 10, a sensitivity analysis is conducted to analyze the impact of unit battery cost u_e on the energy cost. The unit battery cost in the market varies in the range of 800-1800 RMB [50]. It shows that the proposed charging strategy with a 40kWh battery is the most economic one when the unit battery cost is between 1468 to 1800 RMB/kWh. However, as the unit battery cost reduces, higher-capacity battery has a better performance on energy cost. It indicates that a higher capacity battery is potentially promoted as the unit battery cost decreases in the future.

3) COMPARISON OF FOUR SOLVERS

The performance of four outstanding solvers for the wireless charging problem are given in Table 8. Genetic algorithm (GA), particle swarm (PSO), and the proposed algorithm (GWO) are heuristic algorithms [53], while CPLEX is a commercial solver for combinational optimization problems.

Compared with PSO and GA, the solution gap is smallest by using the GWO algorithm. The convergence analysis in Figure 11 also shows that GWO converges fastest. It indicates that the solution performance of GWO is better than that of PSO and GA.

We also compare the proposed GWO algorithm with the CPLEX solver. It is found that the gap between the objective value obtained by GWO and the optimal value obtained by the CPLEX solver is 0.047%. Though the CPLEX solver might get an exact solution, it takes longer computation time than GWO, which is not suitable to real-time computation. Thus, the GWO can find the best solution within an acceptable time more effectively compared with other solvers.

IV. CONCLUSION

This study proposed an en-route wireless charging strategy model for the WCEB system, aiming to optimize the operational energy cost. The battery capacity, the charging start time, and the charging end time were selected as the decision variables in the proposed model. A microscopic power consumption model considering passenger flows was proposed. A relaxation approach based on penalty function and the grey wolf algorithm is utilized to solve the NP-hard problem with complex multidimensional variables and multiple inequality constraints efficiently.

The simulation results demonstrate the effectiveness and efficiency of the proposed model in a real-world bus line. Compared with the instant charging strategy, the total energy cost of a single WCEB can be saved by 13331.26 RMB per year under the charging strategy proposed in this paper. It greatly improves the economic efficiency, which indicates that it is promising to encourage governments or enterprises to promote the WCEB system. Besides, the simulation result shows that the optimal battery capacity is 40kWh, instead of 150kWh with the current unit battery cost. It indicates that it is possible to reduce the operation cost by reducing the battery capacity at the current market price. The solver performance analysis indicates that the proposed GWO can find the best solution within an acceptable time more effectively compared with other solvers.

A sensitive analysis is conducted to investigate the marginal effect of unit battery cost or battery capacity on the charging strategy. It shows that blindly increasing the battery capacity is not a good choice. It is necessary to fully consider the detailed parameters of the road and customize the configuration. In future research, we will apply the proposed charging strategy in a large-scale scenario and further improve the capability of vehicle-to-grid.

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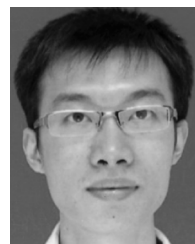
WEILIANG ZENG received the B.Sc. and M.Sc. degrees from the School of Engineering, Sun Yat-sen University, China, in 2009 and 2012, respectively, and the Ph.D. degree from the Department of Civil Engineering, Nagoya University, Japan, in 2016. He is currently an Associate Professor with the Guangdong Key Laboratory of IoT Information Technology, School of Automation, Guangdong University of Technology, China. His research interests include sharable autonomous vehicle, route planning, machine learning, traffic simulation, and transportation dispatch systems.

PANLONG LIU is currently pursuing the master's degree in the Internet of Things and big data with the Guangdong University of Technology under the supervision of Weiliang Zeng. His research interest includes wireless charging electric vehicle charging strategies and decisions.
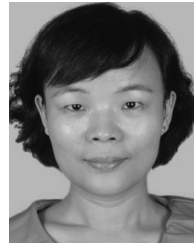
YONGHUI HUANG received the Ph.D. degree in control theory and control engineering from the Guangdong University of Technology (GDUT), China, in 2010. She is a member of the Institute of Intelligent Information Processing, GDUT. Her current research interests include image processing and pattern recognition.
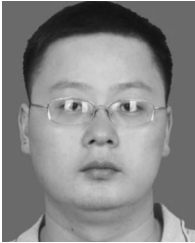
CHAO YANG received the Ph.D. degree in signal and information processing from the South China University of Technology, Guangzhou, China, in 2013. From 2014 to 2016, he was a Research Associate at the Department of Computing, The Hong Kong Polytechnic University, Guangzhou. He is currently with the School of Automation, Guangdong University of Technology.

WEIJUN SUN received the master's degree in computer application from the Nanjing University of Aeronautics and Astronautics, China, in 2003, and the Ph.D. degree from the Guangdong University of Technology (GDUT), Guangzhou, China, in 2020. He is currently a member with the Institute of Intelligent Information Processing, GDUT. His current research interests include pattern recognition and machine learning.
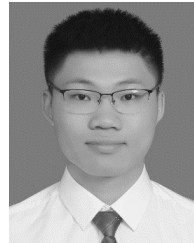
YU HAN is currently pursuing the master's degree in the Internet of Things and big data with the Guangdong University of Technology under the supervision of Weiliang Zeng. His research interests include transportation dispatch systems and machine learning.

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