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Optimal Daily Air Conditioner Usage of an Electric Bus considering Stochastic Travel Times

Yajun Liu[1], Yiming Bie[2]
[1] Master student, School of Transportation, Jilin University, Changchun 130022, China.
E-mail: liuyj155044@126.com.
[2] Associate Professor, School of Transportation, Jilin University, Changchun 130022, China.
E-mail: yimingbie@126.com (corresponding author).

ABSTRACT

The electric bus (EB) has been widely recognized by the public in recent years because of low noise, high driving stability and zero emission. However, EB still has short driving range due to the on-board battery technology. In such condition, the drivers has the driving range anxiety and they dare not turn on the air conditioner (AC) during the operation. To solve this problem, a model is developed to optimize the AC usage of each trip for a given EB. The impact of environmental temperature and AC usage on the coach temperature is quantified. The energy consumption of each trip is estimated based on filed collected data. A chance constrained programming model is then developed considering the stochastic travel times. Maximizing total travel time of the trips that can provide comfortable temperature for passengers is taken as the objective function. Finally, a real bus route is used to validate the proposed method. Results show that the method can provide reliable AC usage scheme under the impacts of stochastic travel times.

Keywords: Electric bus; stochastic travel time; air conditioner usage; optimization model.

1. INTRODUCTION

EB has the advantages of low noise, high driving stability and zero emission. It is of great significance to reduce the emissions of urban vehicle pollutants, the operating costs of transit companies and driver's working load. China has been vigorously promoting the development of EBs in the past 10 years. At present, the number of EBs put into operation accounts for more than 90% of the world. Shenzhen city has replaced all 16000 buses in operation with EBs in 2017, making it the first city to specialize EBs in the world. The number of pure EBs in Guangzhou has reached 10300 by the end of 2018. And 90% of the newly purchased buses in Beijing in 2018 and 2019 are pure EBs. Until the end of 2019, the number of operating EBs in China has reached 0.32 million, accounting for 46.8% of all buses. Besides, it is estimated that the number of operating EBs will reach 0.4 million at the end of 2020.

However, due to the impact of on-board battery technology, EBs still have short driving ranges. Moreover, subject to the land and capital shortage problem, no charging facility is equipped at the origin and terminal stations for most bus lines. Hence, EBs can only be recharged after they return to the depots. It means that the EBs cannot be charged during the operating hours. According to our filed investigation and reports from other references, the energy consumption rate of an EB increases nonlinearly, that is, when the state of charge (SOC) is high, the energy consumption is slower; when the SOC is low, the energy consumption is faster. In this case, bus drivers generally have different degrees of 'anxiety'. They worry that the frequently use of the AC (AC) will accelerate the energy consumption and then lead to service interruption because of the run out of electricity. Even if they know there will be high SOC left (e.g., 40%) at the end of the last trip according to experiences, they dare

Not urn on the AC during the operation, or only turn on the AC in the last few trips. The 'anxiety' pays greatly negative impacts on the travel comfort of passengers and limits the improvement of service level of public transportation.

In recent years, related studies on EB scheduling has been increasing significantly due to the widely implementation of EBs. Current studies mainly focus on the lifecycle costs evaluation[1], driving range estimation[2], charging facilities planning[3], and vehicle scheduling[4]. No scholar has considered the problem of AC usage. According to the statistical data, the average daily operating mileage of EBs in China is 123 km, and the city with the longest average daily operating mileage is Guangzhou (185 km). The ideal driving range of current EBs is about 210 km to 250 km. It can be seen that there will be a certain amount of electricity surplus after the all-day operation, which provides opportunity for the use of AC. The energy consumption of each trip is affected by the SOC at the departure time, trip travel time, temperature, etc. Thus, the use of AC in the previous trip will affect the SOC at the departure time of the next trip, and then the energy consumption. Therefore, it is necessary to consider the number of trips served by a bus during the operating hour, the temperature and travel time of each trip, and establish an optimization model for AC usage. The optimization results are useful to alleviate 'anxiety' of EB drivers and improve the comfort of passengers.

2. MODEL DEVELOPMENT

2.1 Problem description

We assume that an EB needs to operate *N* trips in one day. In this paper, the EB running from the origin station to the terminal station in each direction is defined as a trip. The operation from the depot to the origin station of trip 1 is defined as trip 0, since it needs to consume a certain amount of electricity. The battery SOC at the departure time of trip *n* is denoted by S_n (%). The travel time of trip *n* is h_n, (unit: min), including the route travel time T_n (unit: min) and the waiting time at the terminal station. The environmental temperature $\mu_{OUTn}(t_n)$ and coach temperature $\mu_{INn}(t_n)$ will change with time t_n ($0 \le t_n \le h_n$).

θ_n is a binary variable which represents whether the AC is turned on during the operation of trip *n*. $\theta_n = 0$ means the AC is turned on while $\theta_n = 1$ means the AC is turned off. We assume that the AC is turned off when the bus is waiting at the terminal. Setting integer variable x_n expressed different gears of the AC, which is determined by the parameters of the AC. In the gear x_n, the power of the AC is denoted by $P_{AC}(x_n)$, kW.

During daily operation, the corresponding ambient temperatures of different trips may be quite different. We take the winter as an example. When the ambient temperature is relative high, passengers have slight interest to turn on the AC. Even if the driver turn on the AC, the improvement on passengers' comfort level is limited. However, in low temperature, the passengers have strong desire to turn on the AC and the comfort level will be improved greatly. Therefore, the ambient temperature is selected as a factor for weight w_n in trip *n*. w_n is proportional to the degree that the ambient temperature deviates from the comfortable temperature range, and it can reflect the passenger's desire to turn on the AC. In addition, the travel times of different trips are also different. For example, the travel time in peak hour is larger than that in off-peak hour. Turning on the AC for the trip with longer travel time can increase the comfortable service time and improve the attractiveness of public transport.

Hence, this paper considers the ambient temperature of each trip to set the weight coefficient and establishes the optimization model, which takes the sum of weighted comfortable temperature time enjoyed by passengers in one day as the optimization objective. Whether the AC is turned on and the gear of AC are set as decision variables.

2.2 Chance constrained programming

According to the description in Section 2.1, the objective function and constraints of the model involve travel time T_n, which is a random variable affected by uncertain factors, such as road traffic state, signal timing plans at intersections and passenger demand at stops. In such condition, chance constrained programming (CCP) is a suitable method to model the problem. It is allowed that the decision does not satisfy the constraints to a certain extent, but the decision should make the possibility that the constraints are satisfied not less than the given confidence level[5].

In our study, we need to maximize the value of the objective function and establish the following chance constrained programming model.

$$\max \overline{f} \tag{1}$$

$$\text{s.t.} \begin{cases} \Pr\left\{ f \geq \overline{f} \right\} \geq \alpha \\ \Pr\left\{ S_N \text{-} (E_N / E_A) \times 100\% \geq \lambda \right\} \geq \beta \\ \theta_n = \begin{cases} 0, & \text{if } An \in [\mu_{\min}, \mu_{\max}] \\ 1 \text{ or } 0, & \text{otherwise} \end{cases} \\ x_n \in Z^+, n = 0, \cdots, N \end{cases} \tag{2}$$

where, α and β are predetermined confidence levels. f is the objective function and represents the total time for passengers to enjoy comfortable temperature on all trips, min; $\max \overline{f}$ will be the maximum value that the objective function f achieves with at least possibility α; $\Pr\left\{ f \geq \overline{f} \right\}$ represents probability measure of $f \geq \overline{f}$; E_N represents the energy consumption of the electric bus in the nth trip, kW·h; E_A represents the rated capacity of the electric bus battery; λ is a critical threshold which can ensure that the electric bus has enough battery energy to return to the depot after the end of trip n, %; $S_N \text{-} (E_N / E_A) \times 100\% \geq \lambda$ expresses the SOC value at the end of the nth trip is enough to return to the depot and $\Pr\left\{ S_N \text{-} (E_N / E_A) \times 100\% \geq \lambda \right\}$ indicates its probability measure; A_n means the environmental temperature range within the operation of trip n, $A_n = \left\{ \mu_{OUTn}(t_n) \mid 0 \leq t_n \leq T_n \right\}$; $[\mu_{\min}, \mu_{\max}]$ is the temperature range where passengers feel comfortable, which depends on seasons. When the ambient temperature of the trip n is within the range, it is not necessary to turn on the AC, otherwise, it is considered to turn on it; Z^+ represents the set of positive integers.

2.2.1 Determination of weight

The weight describes the passenger's willingness to turn on the AC, which is directly proportional to the deviation of the ambient temperature from the comfortable temperature. As the ambient temperature changes slowly, the average ambient temperature of trip n is used to calculate the weight w_n.

$$w_n = \begin{cases} \left| \frac{1}{h_n} \int_0^{h_n} \mu_{OUT}(t_n) dt_n - \mu_{\min} \right|, & \frac{1}{h_n} \int_0^{h_n} \mu_{OUT}(t_n) dt_n < \mu_{\min} \\ \left| \frac{1}{h_n} \int_0^{h_n} \mu_{OUT}(t_n) dt_n - \mu_{\max} \right|, & \frac{1}{h_n} \int_0^{h_n} \mu_{OUT}(t_n) dt_n > \mu_{\min} \end{cases} \tag{3}$$

where $\frac{1}{h_n} \int_0^{h_n} \mu_{OUT}(t_n) dt_n$ is the average environmental temperature of the trip n.

2.2.2 Total time enjoyed by passengers within comfortable temperature range

The coach temperature variations are affected by the ambient temperature, the AC and the AC on gear. The variation of the coach temperature μ_{In} with time t_n ($0 \leq t_n \leq h_n$) in the nth trip should satisfy Eq. (4):

$$Q_n(t_n) - Q_n(0) = \frac{Cm\left[\mu_{INn}(t_n) - \mu_{INn}(0) \right]}{60} \tag{4}$$

where $Q_n(t_n) - Q_n(0)$ is the work done by all objects in the time interval [0, t_n] on the air in the coach. C is the specific heat capacity of the air in the coach, kJ/(kg·℃). m is quality of air in the coach, kg. $\mu_{INn}(t_n) - \mu_{INn}(0)$ is the variation of coach temperature by comparing time t_n with time 0, ℃.

Conducting differentiation on t_n to the two sides of the equation, and Eq. (5) is obtained.

$$\frac{dQ_n(t_n)}{dt_n} = \frac{Cmd\mu_{INn}(t_n)}{60 dt_n} \tag{5}$$

The work done by the outside environment on the air in the coach is manifested in two ways: on the one hand, the work done to lower the temperature when the AC is turned on, and on the other hand, the temperature difference between the environment and the coach, which makes the coach temperature tend to be the ambient temperature. As in Eq. (6):

$$\frac{dQ_n(t_n)}{dt_n} = \frac{dQ_{OUTn}(t_n)}{dt_n} - \frac{dQ_{ACn}(t_n)}{dt_n} = \frac{Cmd\mu_{INn}(t_n)}{60 dt_n} \tag{6}$$

where $\frac{dQ_{OUTn}(t_n)}{dt_n}$ is the rate of the change in the environmental work done to the air in the coach. $\frac{dQ_{ACn}(t_n)}{dt_n}$ is the rate of change in the work done by the AC on the coach air, and numerically equals the power of the nth trip $\theta_n \cdot P_{AC}(x_n)$.

In this study, the different heat transfer coefficients of different materials are ignored. The whole heat transfer coefficient of the coach is used and the simplified model in literature [6] is referred. The model considered that the rate of change of the work done by the environment on the coach air was only related to the heat transfer coefficient, the surface area of the coach, and the relative temperature, as shown in Eq. (7):

$$\frac{dQ_{OUTn}(t_n)}{dt_n} = KF\left(\mu_{OUTn}(t_n) - \mu_{INn}(t_n)\right) \quad (7)$$

where K is the average heat transfer coefficient between the outside and the coach, kW/(m^2·℃). F is the contact area between the outside and the coach, m^2.

The continuous function between the coach temperature of the nth trip (μ_{INn}) and time t_n could be obtained by solving Eq. (5). The temperature change during the bus operation on route and the dwell at the terminal station is expressed by Eq. (8).

$$\mu_{INn}(t_n) = \begin{cases} \exp(-\frac{60KFt_n}{mC})\cdot\left[\int [\frac{60KF}{Cm}\cdot\mu_{OUTn}(t_n) - \frac{60\theta_n P(x_n)}{Cm}]\cdot\exp(\frac{60KFt_n}{mC})dt_n + l_n\right] & (0 \le t_n < T_n) \\ \exp(-\frac{60KFt_n}{mC})\cdot\left[\int [\frac{60KF}{Cm}\cdot\mu_{OUTn}(t_n)]\cdot\exp(\frac{60KFt_n}{mC})dt_n + m_n\right] & (T_n \le t_n \le h_n) \end{cases} \quad (8)$$

where l_n and m_n are parameters to be determined. Here we assume that the coach temperature equals the environmental temperature for trip 0, namely $\mu_{IN0}(0) = \mu_{OUTn}(0)$.

Based on the obtained change function of temperature in the coach, the total time that the temperature of the coach is in the comfort range for each trip can be found. Thus, the objective function is obtained as Eq. (9).

$$f = \sum_{n=0}^{N}\left[w_n \cdot \theta_n \cdot len(\{t_n \mid \mu_{\min} \le \mu_{INn}(t_n) \le \mu_{\max}, 0 \le t_n < T_n\})\right] \quad (9)$$

where $\{t_n \mid \mu_{\min} \le \mu_{INn}(t_n) \le \mu_{\max}, 0 \le t_n < T_n\}$ indicates all time ranges that the coach temperature is in range $[\mu_{\min}, \mu_{\max}]$ during the operation of trip n. $len(\{t_n \mid \mu_{\min} \le \mu_{INn}(t_n) \le \mu_{\max}, 0 \le t_n < T_n\})$ represents the length of all the above time ranges.

2.2.3 SOC at the departure time of trip *n*

The amount of energy consumption by an electric bus in trip n is shown in Eqs. (10) and (11).

$$E_n = F_n(S_n, \frac{1}{h_n}\int_0^{h_n} \mu_{OUT}(t_n)dt_n, T_n), n = 0, \dots, N \quad (10)$$

$$E_n' = E_n + \theta_n \cdot P(x_n) \cdot T_n / 60, n = 0, \dots, N \quad (11)$$

where E_n and E_n' are energy consumptions of trip n without and with AC is on respectively, kW·h; $F_n(S_n, \mu_n, T_n)$ is a function involved variables S_n, μ_n and T_n.

The SOC at departure time of trip n is determined by the sum of the energy consumption of previous trips, as shown in Eq. (12).

$$S_n = \begin{cases} (E_{st}/E_A) \times 100\%, & n = 0 \\ \{E_{st} - \sum_{m=0}^{n-1}[\theta_m E_m' + (1-\theta_m)E_m]\} / E_A \times 100\% & , n = 1, \dots, N \end{cases} \quad (12)$$

where E_{st} is the remaining electricity of the electric bus when it leaves the depot, kW·h.

2.2.4 Energy consumption estimation for trip *n* without turning on the AC

Based on filed collected data, three variables that affected the energy consumption of each trip are selected, which are SOC at the departure time, trip travel time and average ambient temperature. E_n is estimated based on Eq. (13).

$$E_n = \hat{\omega}_1 S_n + \hat{\omega}_2 \frac{1}{h_n}\int_0^{h_n} \mu_{OUT}(t_n)dt_n + \hat{\omega}_3 T_n + \hat{\omega}_0 \quad (13)$$

where $\hat{\omega}_1$, $\hat{\omega}_2$, $\hat{\omega}_3$, $\hat{\omega}_0$ are regression parameters fitted by the field survey data.

2.2.5 Impact of randomness on travel time

Statistical results about historical bus trip travel time indicate that travel time T_n can be expressed as a truncated normal distribution following the mean value β_n, variance σ_n^2, lower limit a_n, and upper limit b_n. Its probability density function f is shown in Eq. (14) :

$$f(T_n;\beta_n,\sigma_n,a_n,b_n)=\begin{cases}\dfrac{\frac{1}{\sigma_n}\exp\left[-\frac{1}{2}(\frac{T_n-\beta_n}{\sigma_n})^2\right]}{\exp\left[-\frac{1}{2}(\frac{b_n-\beta_n}{\sigma_n})^2\right]-\exp\left[-\frac{1}{2}(\frac{a_n-\beta_n}{\sigma_n})^2\right]}, & \text{if } a_n\le T_n\le b_n \\ 0 & \text{, otherwise}\end{cases} \tag{14}$$

2.3 Solution algorithm

The traditional way to solve the chance constrained programming model is to transform it into its equivalent form. However, the transform can only be applied in a few special cases. For complex problems, it is difficult to conduct the transform. Hence, in this study the random simulation, neural network and genetic algorithm are combined to solve the proposed model.

Random simulation (also named as Monte Carlo simulation) is a technique used to describe sampling test in stochastic system modeling. It samples random variables based on probability distributions, and it is one effective method for complex problems whose analytical results are not available. In this paper, random simulation is used to calculate probability measures.

The multi-layer forward neural network can be considered as a nonlinear mapping from input space to output space. A forward neural network with one or more neurons is able to approximate a continuous nonlinear function with arbitrary precision.

Genetic algorithm (GA) is a method to find the optimal solution by simulating the natural evolution process. The advantage of genetic algorithm is that it is good at global search and can effectively avoid wandering around the local optimal solution. According to this property, genetic algorithm can be used to generate the weights of neural networks.

The steps of the hybrid intelligent algorithm generated according to the above technologies are displayed as follows:

Step 1: Generate input and output data based on random simulation technology for the uncertain functions, as shown in Eq.s (15) and (16) :

$$U_1(\theta_n,\ x_n):\theta_n,x_n\rightarrow \Pr\left\{S_N\text{-}(E_N/E_A)|\times 100\%\ge\lambda\right\} \tag{15}$$

$$U_2(\theta_n,\ x_n):\theta_n,x_n\rightarrow \max\left\{\overline{f}\,|\,\Pr\left\{f\ge\overline{f}\right\}\ge\alpha\right\} \tag{16}$$

where Eq.s (15) and (16) are used to generate the output $U_1(\theta_n,\ x_n)$ and $U_2(\theta_n,\ x_n)$ respectively based on the input θ_n and x_n.

Step 2: Train a neural network to approach the uncertain function $U_1(\theta_n,\ x_n)$ and $U_2(\theta_n,\ x_n)$ continuously according to the generated input and output data.

Step 3: Initialize the number of chromosomes, and use the trained neural network to test the feasibility of chromosomes.

Step 4: Update chromosomes through crossover and mutation operation, and use the trained neural network to check the feasibility of progeny chromosomes.

Step 5: Use the trained neural network to calculate the target value of all chromosomes.

Step 6: Calculate the fitness of each chromosome according to the target value.

Step 7: Select chromosomes by roulette wheel.

Step 8: Repeat steps 4 to 7 until reach the given number of iterations.

Step 9: Select the best chromosome as the optimal solution.

The parameters of genetic algorithm and neural network should be determined according to the problem. Hence, the values of the parameters are displayed in the case study.

3. CASE STUDY

3.1. Data investigation

The electric bus route 103 in Meihekou city, Jilin Province, China is selected as an example to validate the effectiveness of the proposed optimization method for the usage of AC. This bus route is a loop line and the length is 17 kilometers, with total of 30 stations. The size of the electric bus is 8.5×2.5×3.215 m^3, and the rated battery capacity is 199 kW·h. The heater of the AC can be divided into three gears. The power of the first, second and third degree are 5kW, 7kW and 9kW respectively. There are 13 electric buses on this route, and the timetable of all vehicles can be found in Table 1. The air specific heat in the bus coach is 1 kJ/(kg·℃), the mass is 56.89 kg, and the average heat transfer coefficient is calculated to be 8.4 kW/(m^2·℃). The contact area between the outside and the whole bus carriage is 113.23 m^2.

Data on daily electric bus operations were collected over 15 working days in January 2020, including travel time, energy consumption, ambient temperature, battery SOC at the departure time of each trip, and number of passengers. The temperature in January in Mehekou is relatively low, which can reach as low as -20°C. Therefore, the heating function is the only choice if the driver turns on the AC. The comfortable temperature range is set as [17°C, 22°C] in winter.

Route 103 operates from 6:00 to 17:30 on each day. Of all the 13 EVs, 10 have nine trips and the other three have eight trips per day. The departure time of each trip for each bus is shown in Table 1. It should be noted that trip 0 represents that EBs traveling from the depot to the starting station.

Based on the collected data, a weighted least squares (WLS) fit is used to obtain an estimated energy consumption model for each trip, as shown in Eq. (17).

$$E_n = -3S_n - 0.153\frac{1}{h_n}\int_0^{h_n}\mu_{OUT}\left(t_n\right)dt_n + 0.270T_n - 1.867$$
$$R^2 = 0.957 \tag{17}$$

Table 1. Departure time of each trip for 13 electric buses on route 103

Bus NO.	Trip 0	Trip 1	Trip 2	Trip 3	Trip 4	Trip 5	Trip 6	Trip 7	Trip 8	Trip 9	Trip 10
Bus 1	6:00	6:10	7:20	8:30	9:40	10:50	12:00	13:10	14:20	15:30	16:40
Bus 2	6:05	6:15	7:25	8:35	9:45	10:55	12:05	13:15	14:25	15:35	16:45
Bus 3	6:10	6:20	7:30	8:40	9:50	11:00	12:10	13:20	14:30	15:40	16:50
Bus 4	6:15	6:25	7:35	8:45	9:55	11:05	12:15	13:25	14:35	15:45	16:55
Bus 5	6:20	6:30	7:40	8:50	10:00	11:10	12:20	13:30	14:40	15:50	17:00
Bus 6	6:25	6:35	7:45	8:55	10:05	11:15	12:25	13:35	14:45	15:55	17:06
Bus 7	6:30	6:40	7:50	9:00	10:10	11:20	12:30	13:40	14:50	16:00	17:14
Bus 8	6:35	6:45	7:55	9:05	10:15	11:25	12:35	13:45	14:55	16:05	17:22
Bus 9	6:40	6:50	8:00	9:10	10:20	11:30	12:40	13:50	15:00	16:10	17:30
Bus 10	6:46	6:56	8:06	9:16	10:26	11:36	12:46	13:56	15:06	16:16	—
Bus 11	6:52	7:02	8:12	9:22	10:32	11:42	12:52	14:02	15:12	16:22	—
Bus 12	6:58	7:08	8:18	9:28	10:38	11:48	12:58	14:08	15:18	16:28	—
Bus 13	7:04	7:14	8:24	9:34	10:44	11:54	13:04	14:14	15:24	16:34	—

The travel time of each bus at each trip were collected and thus the parameters of the truncated normal distribution are determined. In this paper, the AC usage scheme for bus 1 is taken as the example. The travel time distribution parameters for each trip of bus 1 are shown in Table 2.

Table 2. Parameters for the trip travel time probability distribution function of bus 1

Parameters	Trip 0	Trip 1	Trip 2	Trip 3	Trip 4	Trip 5	Trip 6	Trip 7	Trip 8	Trip 9	Trip 10
β_n	6	59.4	57.9	55.3	53.6	51.8	52.9	53.8	50.9	52.2	54.2
σ_n	0.5	1.3	1.5	1.4	1.3	1.5	1.5	1.5	1.3	1.4	1.7
a_n	5	50.1	48.6	45.7	46.9	43.7	43.4	45.6	44.2	44.8	42.5
b_n	7	68.8	67.2	64.9	60.3	59.9	62.4	62.0	57.6	59.6	65.9

The initial SOC when the bus departs the depot is denoted by S_0, which is equal to 100%. λ, α and β are set to be 5%, 0.9 and 0.8 respectively. Table 3 shows the trip travel time and average ambient temperature for each trip on January 13, 2020.

Table 3. Trip travel time and temperature on Jan.13, 2020

Parameters	Trip 0	Trip 1	Trip 2	Trip 3	Trip 4	Trip 5	Trip 6	Trip 7	Trip 8	Trip 9	Trip 10
h_n	10.0	71.8	70.8	69.8	70.2	70.0	70.3	70.0	70.4	71.2	71.5
$\frac{1}{h_n}\int_0^{h_n}\mu_{OUT}\left(t_n\right)dt_n$	-10.5	-8.4	-6.3	-5.3	-4.3	-3.2	-4.6	-5.6	-5.8	-6.0	-8.2

3.2. Results analysis

Initialized parameters in the solution algorithm of Section 2.3 are shown as follows: the population size is 30, crossover rate is 0.3, mutation rate is 0.2; number of input neurons is 33, number of hidden layers is 1, number of neurons in hidden layers is 30, number of input neurons is 2. The number of simulation cycles is 5000, number of training samples is 3000, the number of genetic iterations is 200 for the hybrid intelligence algorithm.

Based on the data given in Section 3.1, the optimal solution for bus 1 is obtained and shown in Eq. (18):

$$
\begin{aligned}
&(\theta_0^*,\theta_1^*,\theta_2^*,\theta_3^*,\theta_4^*,\theta_5^*,\theta_6^*,\theta_7^*,\theta_8^*,\theta_9^*,\theta_{10}^*,x_0^*,x_1^*,x_2^*,x_3^*,x_4^*,x_5^*,x_6^*,x_7^*,x_8^*,x_9^*,x_{10}^*) \\
&=\left(1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 2,\ 2,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 2,\ 2\right)
\end{aligned}
\tag{18}
$$

The target value $\overline{f}^*$ =9976.48. Specifically, probability measure is also obtained and shown in Eq. (19):

$$
\begin{aligned}
&\Pr\left\{ f \geq \overline{f} \right\}=0.907 \\
&\Pr\left\{S_N\text{-}(E_N/E_A)\times 100\% \geq 5\%\right\}=0.953
\end{aligned}
\tag{19}
$$

According to Eq. (18), for all trips of bus 1 on January 13, 2020, the AC usage are displayed as follows: turn on the AC in trips 0 to 4 and trips 7 to10, in addition, switch to 2nd gear in trip 0, trip 1, trip 9 and trip 10. Under this circumstance, battery energy can be utilized to the maximum, in the meantime, the objective function f achieves the maximum value with 9976.48 at least possibility α, the probability that the vehicle can return to the depot after the last trip is 0.953.

4. CONCLUSION

The use of the air conditioner is one basic need for an electric bus, especially in summer and winter. This study developed a model to optimize the AC usage while maintaining the daily operation of the EB. The stochastic travel times of the trips are considered to improve the reliability of optimization result. The following conclusions can be drawn:

(i) The comfort level of passengers is affected by multiple factors, such as the environmental temperature, the work of AC and the number of passengers in the coach. The calculation model for the inside temperature is the critical issue of this study.

(ii) The stochastic travel time should be considered during the optimization. It is mainly because the stochastic travel time will result in the stochastic energy consumption during the operation and the estimation results for energy consumption would affect the usage of AC.

(iii) For most EBs, it is unable to turn on the AC for all trips without charge. In such condition, it is important to decide on which trips the AC can be turned on. If the EB can't be charged during the operating hours, then it is better to turn on the AC when it is needed.

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