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電動機車使用者電池交換行為之離散事件系統模擬[1]

DISCRETE-EVENT SYSTEM SIMULATION OF BATTERY SWAPPING BEHAVIORS FOR ELECTRIC SCOOTER DRIVERS

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摘 要

機車為臺灣的主要運輸工具之一，近年來隨著環保意識的抬頭，政府致力於電動機車的普及化，然而，電動機車之行駛續航力較傳統運具為低，使用者在一段使用期間內就必須進行補給能源，因此，電動機車能源補充之方便對於其普及有極大影響。電池交換為電動機車能源補給的常見方式之一，其優點為能源補給僅需數分鐘甚至是數秒，車上亦可以存放備用電池以提昇續航力。由於補助能源的方便與否為使用者選擇電動機車的重要考量，本研究以電池交換形式之電動機車為主要研究對象，建構電動機車電池交換系統 (包含：電動機車使用者、電池、以及電池交換站) 之離散型事件模擬模式，可用於分析評估系統之運作效能。本研究之案例測試係以模擬模式為基礎，進行電池交換站的位置以及容量之最佳化，最後進行敏

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感度分析，以了解預算、換電池門檻、電力消耗率、充電率等因素對充電站選址之影響，結果顯示本研究所建構之模擬模式具有輔助電動機車系統之各項規劃設計評估工作之潛力，有助於電動機車之推廣與普及。

關鍵詞： 電動機車; 選址問題；換電系統；基因演算法；離散事件系統模擬；隨機規劃

ABSTRACT

Scooters are one of the major transportation modes in Taiwan. Apart from raising environmental consciousness, the government has been devoted to popularizing electric scooters. Compared with gasoline-fueled scooters, electric scooters have a lower driving range and require more frequent refueling. One of the approaches to refuel electric scooters is to swap batteries at a battery swapping station. The advantage of this approach is that it takes only minutes or seconds to complete. Backup batteries may also be stored in scooters to extend their driving range. This study focuses on electric scooters adopting the battery swapping approach. As the efficiency of refueling is one of the main concerns of electric scooter users, this study develops a discrete-event system simulation model for the battery swapping systems of electric scooters, which include scooter users, batteries, and swapping stations. The model can be used to analyze the performance of battery swapping systems. In a numerical example, the simulation model is applied to optimize the location and capacity of swapping stations. A sensitivity analysis is conducted to further understand the effects of factors such as budget, power threshold of swapping batteries, power consumption rates, and battery charging rates on the locations of swapping stations. The simulation model is shown to have the potential to aid the planning and design of electric scooter systems and benefit the popularization of electric scooters.

Key Words: *Electric scooters; Location problem; Battery swapping system; Genetic algorithm; Discrete-event system simulation; Stochastic programming*

I. Introduction

Environmental awareness has heightened recently. As a result, electric vehicles (EVs) have become increasingly popular because they are considered environmentally friendly. Scooters are one of the major transportation modes in Taiwan. Apart from raising environmental consciousness, the government has been devoted to popularizing electric scooters. According to statistics, the yearly number of new electric scooter subsidies, essentially the number of newly purchased electric scooters, continues to climb, even reaching 39,000 in 2017 (Fig. 1) (Industrial Development Bureau, Ministry of Economic Affairs in Taiwan [1]).

Despite the promising qualities of electric scooters, this mode of transportation still has some disadvantages. One of the major drawbacks obstructing the market penetration of electric scooters is their low driving range relative to gasoline-fueled scooters. The battery capacity of electric scooters restricts the range of their use, and this drawback leads to a phenomenon called *range anxiety* (Dong, Liu and Lin [2]; ElBanhawy and Nassar [3]; Nie and Ghamami [4]). Range anxiety means that, due to the short driving distance of EV, EV users, including users of electric scooters, worry about running out of battery in the middle of their travel and thus the anxiety of EV users increases as they travel away from charging stations. Another obstacle to the popularity of electric scooters is the inconvenience of refueling. Traditionally, EVs are designed to be charged at recharging stations. Refueling electric scooters is generally more time consuming than refueling gasoline-fueled scooters is, especially when the battery charging rate is low or the charging infrastructure is limited. The long refueling time also prevents EV users from refueling in the middle of work-related trips.

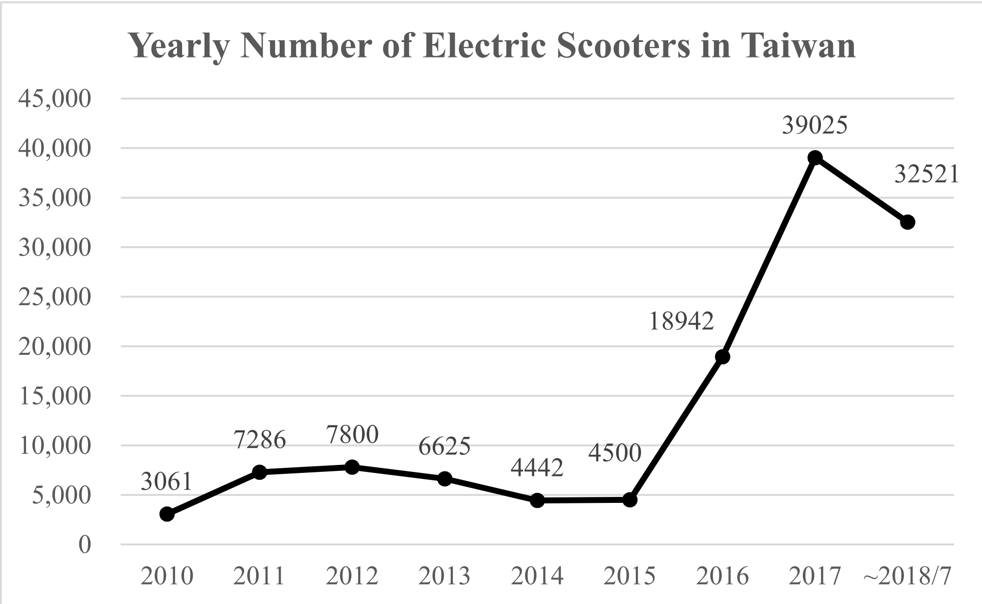

Fig. 1 Yearly number of new electric scooter subsidies in Taiwan (Industrial Development Bureau, Ministry of Economic Affairs in Taiwan [1]).

As a solution to the issue of long refueling time, a battery swapping system has been developed as an alternative to charging stations. The system reduces the refueling time from hours to only a few minutes or even seconds (Zheng, Dong, Xu, Meng, Zhao and Qiu [5]). This innovative design significantly increases the attractiveness of EVs. The swapping system also allows refueling in the middle of a trip (Mak, Rong and Shen [6]). Previous works related to battery swapping for EVs include those of Zheng, Dong, Xu, Meng, Zhao and Qiu [5], Mak, Rong and Shen [6], McPherson, Richardson, McLennan and Zippel [7], Yang and Sun [8], Wang [9] and Hof, Schneider and Goeke [10]. These studies mainly focused on the optimization of station locations with consideration of the driving distance between recharges. Other factors considered in the optimization include the power thresholds of refueling (McPherson, Richardson, McLennan and Zippel [7]), multiple battery swaps in a trip (Yang and Sun [8]; Hof, Schneider and Goeke [10]), stochastic arrival rate of users (Mak, Rong and Shen [6]; Zheng, Dong, Xu, Meng, Zhao and Qiu [5]), stochastic initial power level (McPherson, Richardson, McLennan and Zippel [7]), and capacitated refueling facility (Hof, Schneider and Goeke [10]; Zheng, Dong, Xu, Meng, Zhao and Qiu [5]).

The present study develops a stochastic discrete-event simulation (SDES) model to describe a battery swapping system for electric scooters. SDES reproduces other complicated operations of battery swapping for real-world sized problems. Battery swapping stations are queuing systems by nature and can thus be properly captured by SDES. Furthermore, the major stochastic factors of battery swapping systems mentioned previously, such as the stochastic arrival rates of users and initial power levels, are considered simultaneously in the proposed model, the first to do so in the literature. By contrast, existing studies that adopted mathematical models considered highly simplified behaviors and/or limited problems (Mak, Rong and Shen [6]; Yang and Sun [8]). Accordingly, SDES is selected as the main methodology for the present study.

To demonstrate the applicability of the proposed SDES, we use the simulation model in a numerical example to optimize the location and capacity of battery swapping stations because the allocation of charging facilities is one of the major factors affecting the usage rate of EVs (He, Kuo and Wu [11]; Zhang, Kang and Kwon [12]; and Ge, Feng, Liu and Wang [13]). The proposed SDES is capable of predicting efficiently the critical indicators of system service levels, such as the arrival rates and utilization levels of battery swapping stations and the average traveling distance and waiting times for users given the locations of swapping stations. Combined with an optimization procedure, the SDES serves as a useful tool to determine the proper deployment of battery swapping stations for electric scooters. The effects of factors such as budget, power thresholds of swapping battery, power consumption rates, and charging rates on the locations of swapping stations are further studied through a sensitivity analysis. The numerical example shows that the SDES could aid the planning and design of electric scooter systems and benefit the popularization of electric scooters.

II. SDES model

This section describes the development of the SDES. Section 2.1 states the model assumptions. Section 2.2 describes the user behaviors and the randomness in the model. Section 2.3 discusses the model implementation. Section 2.4 defines the performance measure.

2.1 Model assumptions

The model considers a well-established battery swapping system and electric scooter users with stable travel patterns (e.g., daily commuters) and familiarity with battery swapping systems. Therefore, the following assumptions are made in the SDES model to establish a reasonable simplification of the problem and improve computational efficiency.

1. Following Hodgson [14], this study considers the travel demands of electric scooter users as exogenous and not influenced by the locations of battery swapping stations.
2. The origin and destination (OD) pair of each scooter user is known.
3. The travel path and travel time of an OD pair are known (Hodgson [14]).
4. Users can estimate the consumption of battery power by travel distance.
5. According to the website of a major electric scooter company, users commonly have two preferred stations and only use them for battery swapping (Gogoro Inc. [15]). Therefore, each user is assumed to consider only their preferred stations for battery swapping.
6. The number of attempts of battery swapping by a user is limited. If the user fails to secure a battery with satisfactory power level within the number of attempts, the user will leave the electric scooter at the station and complete the trip with other transportation modes, such as a taxi or bus. This assumption prevents a user from continuously searching for a battery and not completing their trips when such batteries are unavailable.
7. Battery chargers are identical. That is, they have the same battery capacities and charging rates. However, the number of batteries stored in the charger could vary between stations.
8. The deterioration and failure of batteries, chargers, and swapping stations are not considered.

2.2 Model description

2.2.1 User behaviors

This section defines the main behaviors of travel and battery swapping of the users in the simulation system. Naturally, the power of a battery is consumed when a user travels on a scooter from the origin to the destination. Before a user starts the trip, the user forecasts the power consumption first. If the power level triggers the threshold of the power level for battery swapping before completing this travel, the user will swap a battery first and complete the travel later. This procedure reflects the user’s range anxiety.

The battery swapping behaviors of a user given a maximum of two attempts to swap batteries are depicted in Fig. 2. If the user decides to swap the battery upon arriving at one of the preferred stations (Station A), this user lines up in accordance with the first-in, first-out rule. The battery swapping at the first station that the user visits is called *first battery swapping*. If any idle charger is available, the user occupies it. The state of the charger becomes busy and the charger fills the battery. Two possible outcomes might follow. First, the user secures a battery with satisfactory power level. Then, the user continues to travel, and the state of the charger becomes idle. This outcome is considered a *successful* first battery swapping. Second, the user gets a battery with unsatisfactory power level. Then, the user moves to another station (Station B) if possible. Such behavior is called *second battery swapping*, and it can only be performed if the following conditions are satisfied: (1) the current power level of the battery is sufficient to move to the second swapping station and (2) the total time of swapping (first plus second) remains within a tolerable value. If the user makes a successful swap for a battery with satisfactory power level in Station B, a *successful* second battery swapping is conducted. If the above two conditions are not satisfied, the user has no choice but to line up at the same station and wait for batteries to charge.

Finally, the attempt to swap batteries terminates if the total time of battery swapping exceeds the maximum tolerable value. In this case, the user runs out the patience and gives up the swapping. The user leaves the electric scooter at the station and uses other modes to reach the destination.

2.2.2 Randomness

The two sources of uncertainty in the stochastic simulation model are the departure time of users and the initial power level of batteries. These factors have significant impact on the need for battery swapping and on user arrival rates in swapping stations. However, they are highly variable in the real world and extremely difficult to precisely predict. Therefore, they are considered as random variables in the SDES model. Section 3.1 discusses the probability distributions followed by the two sets of random variables.

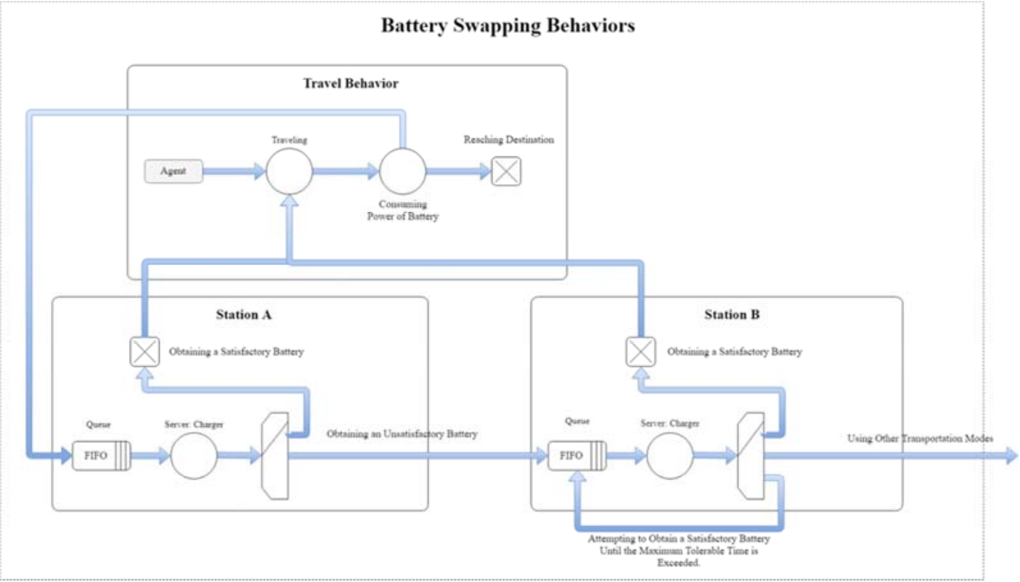

Fig. 2　Flowchart of battery swapping behaviors.

2.3 Model implementation

To keep a high maintenance capability, this research adopts the programming paradigm called object-oriented programming (OOP). In particular, the unified modeling language (UML) is utilized to express the procedure of functions. Fig. 3 illustrates the UML class diagram of the battery swapping system. Three kinds of classes exist: Agent (EV user), Battery, and Swapping Station. These classes can be recognized as templates, and different entity objects in the system are created through the corresponding classes. The different entity objects have their own attributes and methods. Remarkably, the attributes and methods of an agent are substantially greater than those of the other classes because a meticulous depiction of the usage behavior of users is necessary.

The interaction of these three entity objects constitutes an event. Three different categories of events exist. The first category of events handle the system changes due to traveling of a user, which is illustrated in Fig.4. In the event, a user determines whether the power level of the battery is sufficient to complete the trip. If it is sufficient, the user moves to the destination. If not, the user selects a battery swapping station and moves toward to that station. The related attributes are updated and corresponding events are generated. The second categories of events handle system changes due to the battery swapping of a user. The procedure of the events is illustrated in Fig. 5. The event states that, when a user arrives the station, the user transfers the currently owned battery to the station and the battery with the highest power level is returned to the user. The related attributes are then updated. Next, SatisfactionCheck() is called to check whether the user is satisfied with the power level of the swapped battery. If the user is satisfied, the user continues the trip and moves to the destination. If the user is not satisfied and another attempt to swap battery is possible, the user goes to another station to swap the battery. If the user is not satisfied but another attempt is not possible, the user waits for the battery to charge. The waiting continues until the maximum tolerable time is exceeded and the user leaves the station and moves to the destination with other transportation modes. The third categories of events handle the system changes regarding the situation where a user waits at a station for the battery to charge, which is illustrated in Fig. 6. The event states that, when a user decides to wait at the station for the battery to charge, one of the batteries is reserved for the user and cannot be swapped by other users.

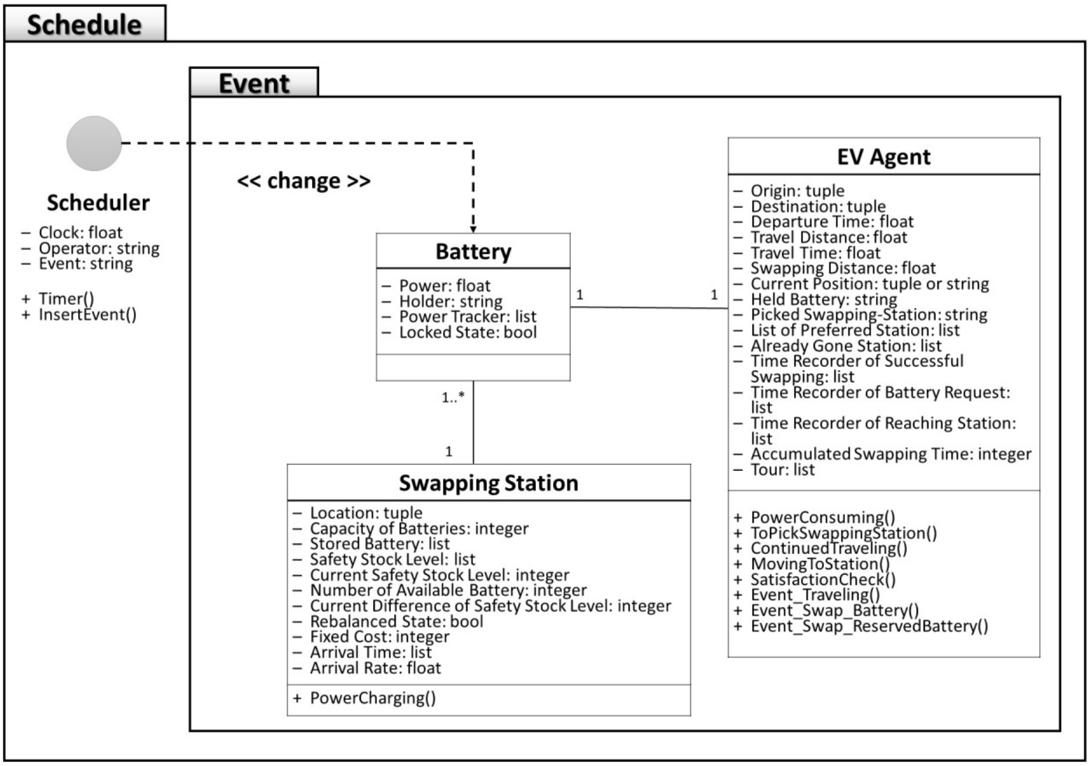

Fig. 3 UML class diagram of battery swapping system.

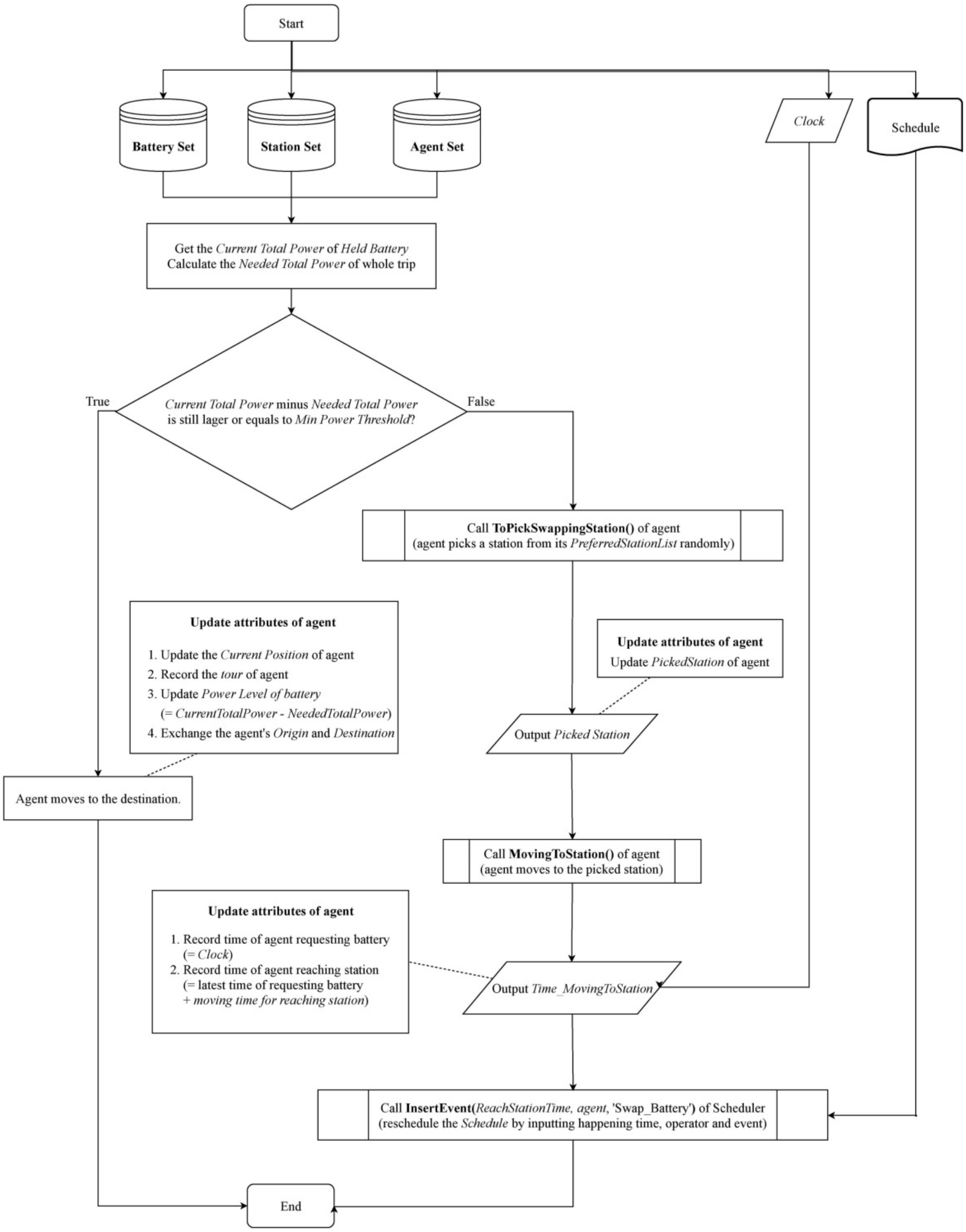

Fig. 4　Event flowchart—Traveling of a user.

A schedule is maintained to track events and enable a chronological implementation of the simulation. The responsibility of the “scheduler” in the schedule package is to execute rescheduling. The “Timer” function is to identify and return the next event, its correlative operator, and happening time (clock) in the schedule to the SDES. Then, the SDES can simulate

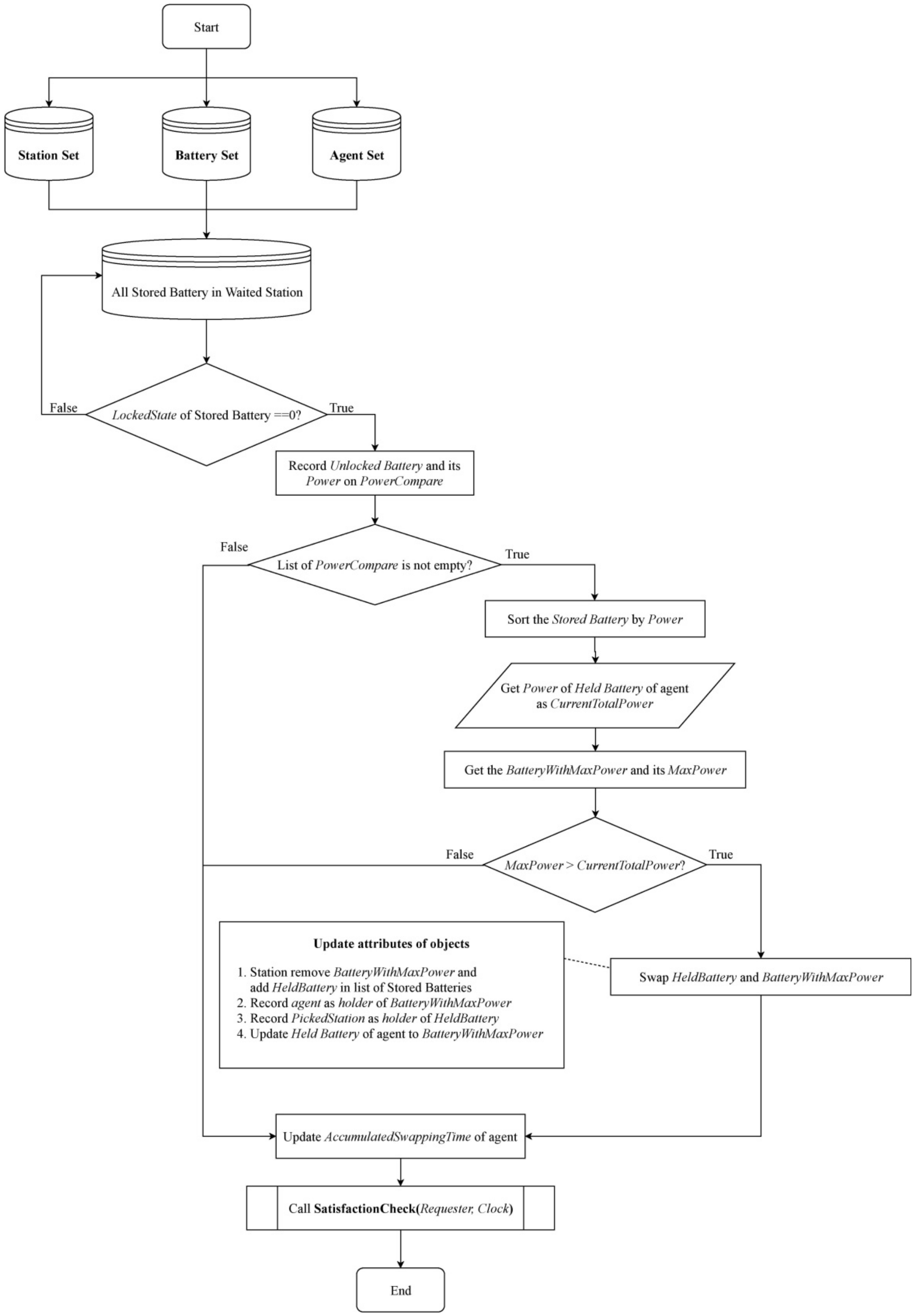

Fig. 5 Event flowchart—Battery swapping of a user.

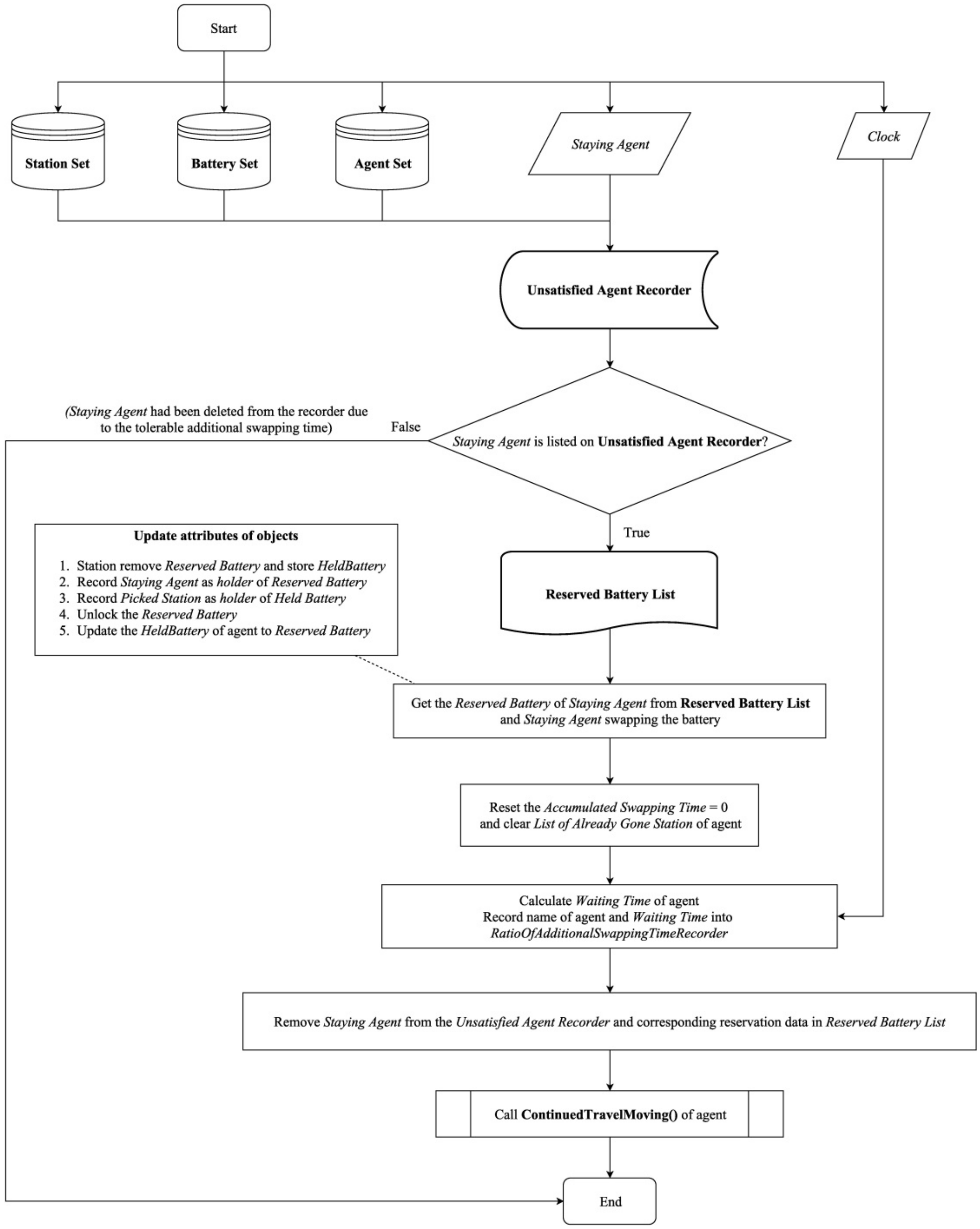

Fig. 6　Event flowchart—Reserved battery swapping of a user.

this next event. Notably, if a new event is generated, the “InsertEvent()” function is called to insert the new event to the schedule according the time of the event. Owing to the large number of events, searching the correct insertion position in the entire schedule is cumbersome. Thus, the bisect algorithm is adopted in the function. The bisect algorithm keeps dividing the schedule into two sections and compares the happening time of the median event and that of the new event until it determines the correct insertion position.

2.4 Performance measure

The performance measure of a battery swapping system of electric scooters is defined as $\frac{x_1}{d_1} + \frac{x_2}{(d_2)^{\alpha}} - \frac{y}{(d_3)^{\beta}}$, where

x_1 : the ratio of successful first battery swapping

x_2 : the ratio of successful second battery swapping

y : the ratio of unsuccessful swapping

d_1 : total standardized travel distance of successful first battery swapping

d_2 : total standardized travel distance of successful second battery swapping

d_3 : total standardized remaining distance of unsuccessful swapping

α : the degree of penalty for the total travel distance of second battery swapping

β : the degree of penalty for the total remaining distance of unsuccessful swapping

System performance comprises three terms. The first two terms are the ratio of successful first battery swapping (x_1) and the ratio of successful second battery swapping (x_2). They represent the probability that a user swaps a battery with satisfactory power level. Clearly, a high value is desired; thus, both terms have positive signs. To reflect the inconvenience of swapping batteries, the first two terms are discounted by the total travel distance for swapping (d_1 and d_2). Furthermore, to favor the first swapping over the second swapping, travel distance for second swapping (d_2) is raised to the power of α (> 1) to further discount the term for second swapping. The third term is the ratio of unsuccessful swapping. Unsuccessful swapping is clearly undesired; consequently, the term has a negative sign. Similar to the first two terms, travel distance requires consideration. Given that the penalty for an unsuccessful swapping comes from the inconvenience of leaving the scooter and taking another transportation mode to complete the trip, the distance used in the third term (d_3) is the remaining distance of the trip. Furthermore, it is the most unattractive among the three terms; thus, the absolute value of β (the power of d_3) must be greater than α. That is, $|\beta| > \alpha > 1$. Moreover, the power of d_3 must be negative; thus, the negative effect of the ratio increases as the distance increases. Notably, all the distances in the performance measure are standardized. The total travel distances are different for users. To evaluate the performance of the system fairly, we divide the travel distance of a swapping by the original travel distance of the trip before its use in the performance measure.

III. Numerical example

To validate the proposed model, we use it to optimize the location and capacity of battery swapping stations for a hypothetical example. With this example, the important factors of deploying swapping stations can be revealed. The computational environment is a desktop computer with Windows 10 operating system, Intel i7-7700 CPU @3.6 GHz and 16 GB RAM.

3.1 Input data of SDES

The current study defines the parameter setting of SDES in three categories.

3.1.1 Demand data

The required demand data include OD matrices and the distribution of departure times of users. The nodes in Fig. 7 denote the traffic zones of the hypothetical transportation network. The values in the rectangular boxes indicates the traffic zone numbers. The total number of users in the system is 608. The daily travel demands using electric scooters between the traffic zones are generated randomly. According to an interview with a major electric scooter company in Taiwan, electric scooter users normally swap batteries every three days. Given the total travel demands and the frequency of battery swapping, the demands requiring a battery swapping can be estimated, where are summarized in Table 1 and shown in Fig. 7. The black lines indicate the flow volume between each OD pair, and they become thick if the volume is heavy. The average travel distance of OD pairs is set to 8.75 km in this hypothetical distribution. The number is close to the average distance of a passenger carried in urban areas of Taiwan (8.6 km) according to the transportation statistical database (Ministry of Transportation and Communications in Taiwan [16]). The daily demands are distributed into morning-peak, off-peak, and afternoon-peak periods given a ratio of 2:1:2 approximately, which are not displayed to save space.

Table 1　Hypothetical daily OD demands requiring a battery swapping

O/D	1	2	3	4	5	6	7	8	9	10	Total
1	19	5	3	11	3	13	13	8	3	8	86
2	5	11	8	11	8	13	16	13	11	13	109
3	3	8	3	5	5	5	11	11	5	8	64
4	11	11	5	5	11	5	16	8	11	8	91
5	3	8	5	11	8	11	13	13	13	11	96
6	13	13	5	5	11	13	5	11	16	13	105
7	13	16	11	16	13	5	13	8	16	13	124
8	8	13	11	8	13	11	8	0	8	11	91
9	3	11	5	11	13	16	16	8	13	8	104
10	8	13	8	8	11	13	13	11	8	11	104
Total	86	109	64	91	96	105	124	91	104	104	974

The distribution of departure time adopted in this research is based on the research conducted by Shiu [17]. Fig. 8 shows the distributions of departure times in different cities and periods. On the basis of this figure, we assume that the departure times of morning and afternoon peaks follow truncated normal distributions and that the departure times of the off-peak hours follow a uniform distribution. Table 2 lists the detailed settings for departure time. That is, the departure time of a user in the morning-peak period is randomly generated by a truncated normal distribution with a mean of 08:00, a standard deviation of 1 hour, and an interval of (07:00, 09:00). The departure time of a user in the off-peak period is randomly generated by a uniform

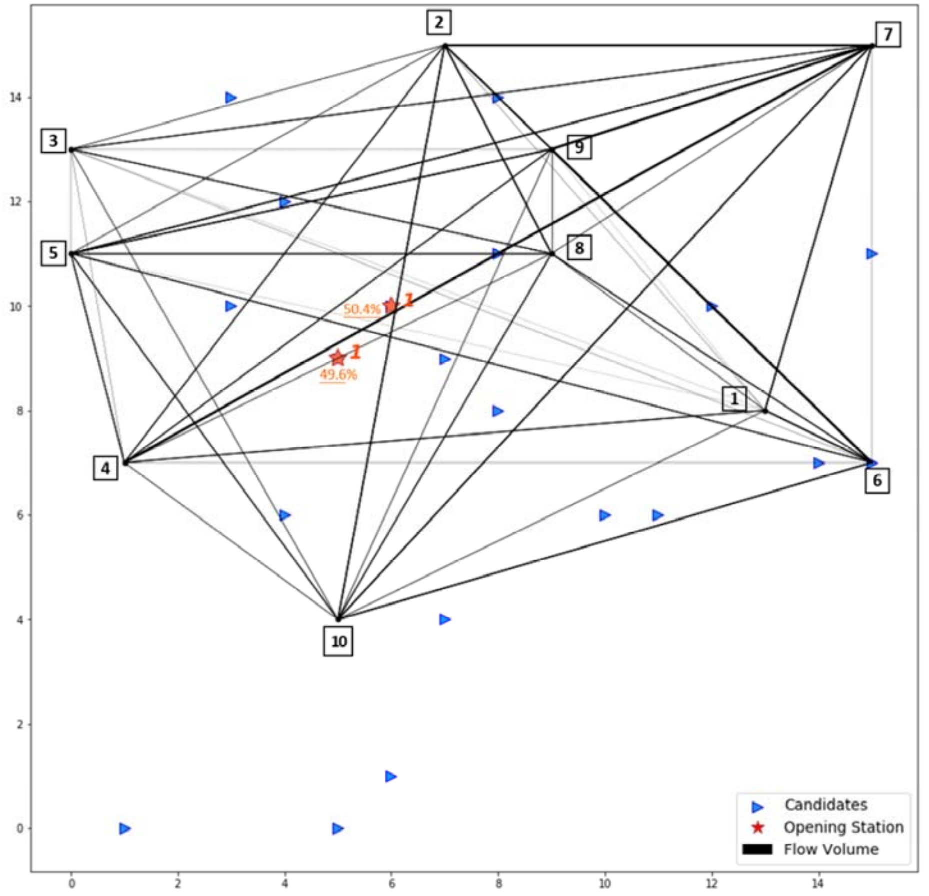

Fig. 7 Hypothetical travel demand and site selection.

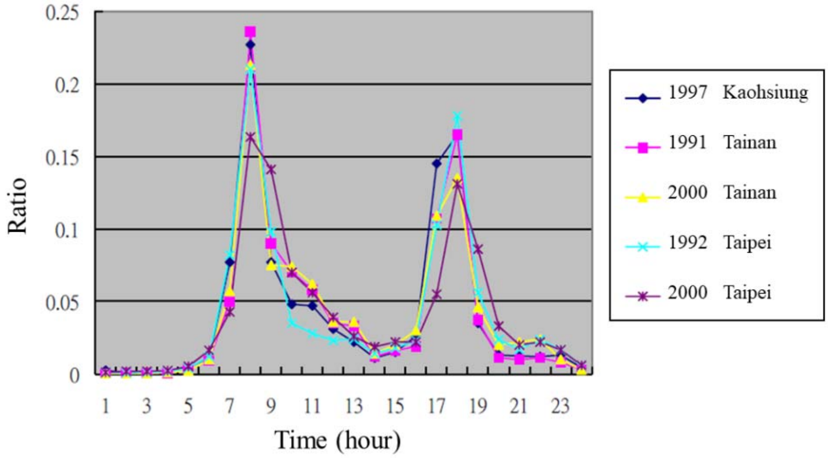

Fig. 8 Comparison of the distributions for departure time in different cities (Shiu [17]).

Table 2　Parameters of distribution for departure time

Period	Interval	Type of Distribution	Mean	Standard Deviation
Morning-peak	07:00 - 09:00	Truncated Normal Distribution	08:00	01:00
Off-peak	09:00 - 16:30	Uniform Distribution	–	–
Afternoon-peak	16:30 - 19:30	Truncated Normal Distribution	18:00	01:30

distribution between 09:00 and 16:30. The departure time of a user in the afternoon-peak period is randomly generated by a truncated normal distribution with a mean of 18:00, a standard deviation of 1 hour, and an interval of (16:30, 19:30). The simulation time is 7:00–20:00, which is consistent with the period of daily commutes.

3.1.2 Usage behavior

The travel speed of users is set to 40 KPH. The travel times between OD pairs are calculated on the basis of this speed and the travel distance. According to an interview with a major electric scooter company in Taiwan, the threshold that triggers battery swapping is nearly 40%, and the satisfactory power level for users is approximately 70%. Given that the electric scooter company hopes that every user can obtain a satisfactory battery within two attempts of battery swapping, we set the maximum number of battery swapping attempts to 2. In addition, the maximum tolerable time spent for battery swapping is 5 min. Finally, the preferred stations for a user are those nearest to the travel path between the OD of the user, as illustrated in Fig. 9. Finally, the initial power levels of batteries follow the uniform distribution between the threshold for battery swapping and the full value.

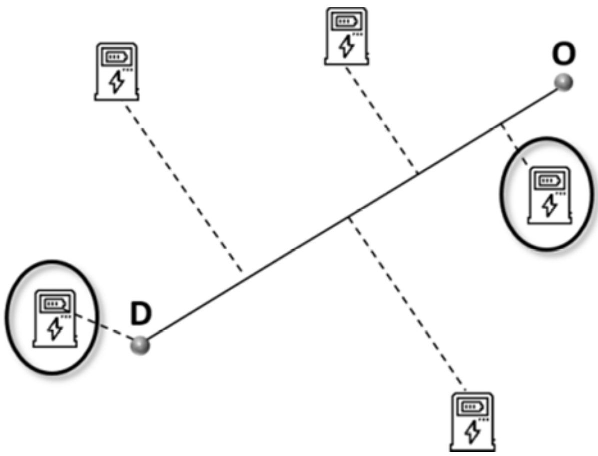

Fig. 9　Preferred Stations of an O-D Pair.

3.1.3 Operating information

According to the interview with the company, operational parameters are determined as follows. The fixed cost of each charger is estimated to be 500,000 NT dollars. Each charger in the station stores up to three sets of batteries. The charging rates of the batteries are approximated by a piecewise linear function, as shown in Fig. 10. Recharging the batteries from 0% to 70% only requires approximately 30 min using the charger in the stations. Charging from 70% to 90% requires an additional time of 150 min. The discharging rate is 0.01% every second under 40 KPH.

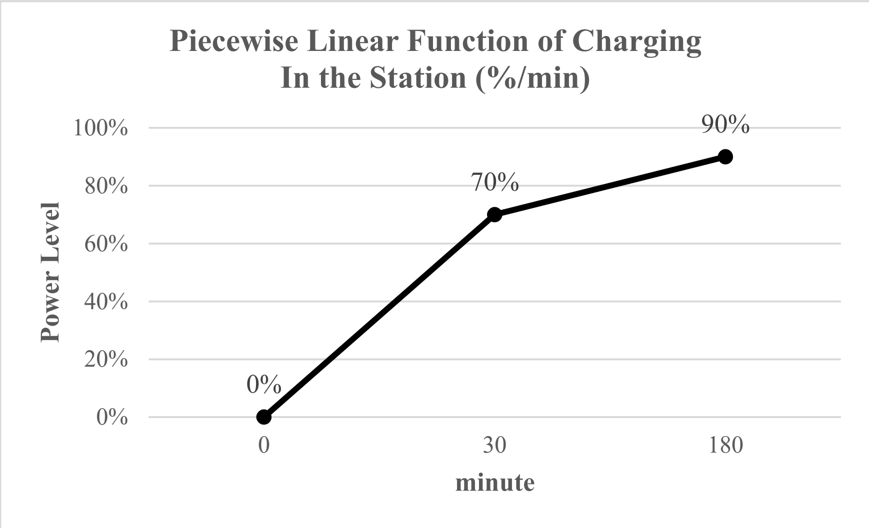

Fig. 10 Piecewise linear function of charging rate.

3.2 Applying to SDES to location problems

The proposed SDES model simulates the swapping system given the site selection of swapping stations so that it can be used to analyze and improve the operations of swapping systems in various ways. To demonstrate the model's applicability, we adopt the SDES for the location optimization of battery swapping stations. Notably, the location optimization utilizing the SDES model is consistent with the flow interception models in the literature, which consider refueling in the middle of a travel (McPherson, Richardson, McLennan and Zippel [7]; Mak, Rong and Shen [6]; Wang [9]). Unlike the system of recharging stations in which charging commonly occurs at the two end nodes of the trip, refueling frequently occurs in the middle of a travel for battery swapping systems. Therefore, flow interception models are realistic to optimize the battery swapping stations of electric scooters.

The optimization method adopted in this research is genetic algorithm (GA), which is one of the commonly used optimized methodologies for location problems. The performance measure defined in Section 2.4 can be used as the *fitness function* in GA. In this numerical example, the degree of penalty on second battery swapping (α) is set to 1.0003, and the degree of penalty on unsuccessful battery swapping (β) is given as −1.0005 in the fitness function. The decision variables of the location problem are the quantities of batteries stored in the swapping stations. Since a charger can store up to three sets of batteries, the possible values of the decision variables are 0, 1, 2, and 3. The candidate locations of swapping stations are indicated by the triangles and stars in Fig. 7. The penalty method is adopted to handle infeasible solutions. When a solution (a selection of stations) is generated, its feasibility is verified. The feasibility involves two checks: whether the number of opening stations is within the limit and whether the total fixed cost is within the total budget. The fitness score of the solution is a large negative penalty, and the SDES is not executed. If the selection is feasible, Algorithm 1 is executed.

As random variables are involved in the SDES, the simulations must be repeated to calculate the expected fitness score. If the solution is feasible, Algorithm 1 is executed to calculate the expected fitness score of the solution. The SDES is first initialized. The main task in the initialization is to determine the preferred stations for each user given the current solution. The random numbers are generated for the random variables, namely, departure times and initial power levels. Then, the battery swapping of users is simulated. After the simulation is complete, the fitness score of a scenario is calculated and recorded. Subsequently, another set of random numbers are generated again, and the simulation is repeated until the number of samples of random numbers reaches meets the requirement. Finally, the average of all the fitness scores is calculated and returned to the GA.

In the numerical example, the GA optimization is performed using the Pyevolve library. The number of generations is set to 100, and the population size is 20. In each evaluation of a solution, the SDES are repeated 100 times to calculate the expected fitness score. This value is decided on the basis of preliminary testing shown in Fig. 11. The figure presents the plot of the standard errors of the mean fitness of the selected solution versus the number of samples. The plot shows that the standard error is generally stable after 100 samples. Therefore, the required number of samples of a random number for each solution evaluation is set to 100 in GA. The analysis of the results of the location problem is discussed below.

3.3 Results

As an example of the solution of the location optimization using the SDES, the chosen locations for swapping stations given 1 million dollars are indicated by the two stars in Fig. 7.

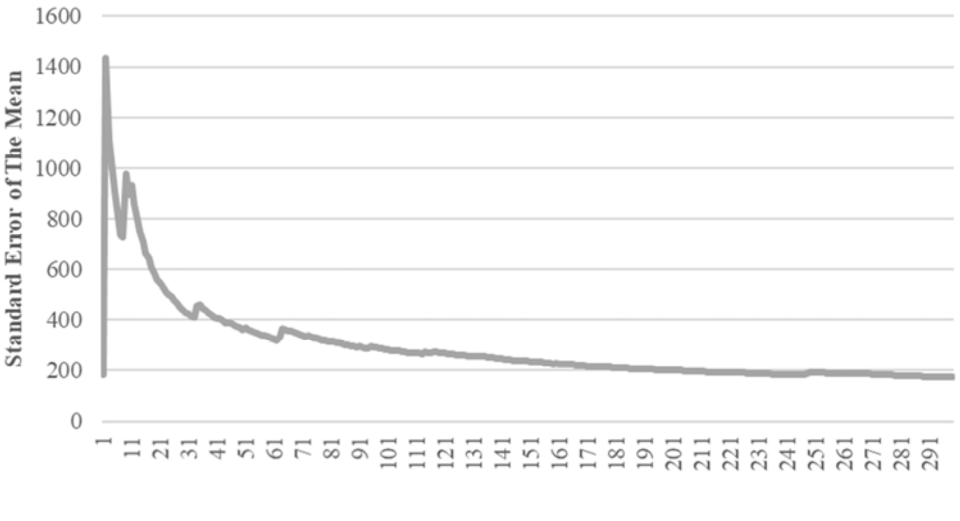

Fig. 11　Standard error of the mean fitness versus number of samples.

```
Input  : chromosome
Output: Score
while SampleSize < Maximum of Sample Size do
    Initialize Environmental Variables for SDES under a certain scenario
    Randomly pick DepartureTime of users and InitialPowerLevel of
      batteries under this scenario // two stochastic factors
    According to the DepartureTime, adding the Event of TravelMoving
      into Schedule chronologically
    while Clock < SimulationTime and Schedule is not empty do
        (Clock, operator, NextEvent) = Timer() // Grab an Event
        /* Check whether staying agents are still waiting or
           already had taken other modes to the destination in
           row                                  */
        if Unsatisfied Agent Recorder is not empty then
            for StayingAgent, StartingWaitingTime do
                if AccumulatedWaitingTime >= Tolerable Additional
                  Time for Swapping then
                    StayingAgent uses other modes moving to the
                      destination and the Penalty is generated
                else
                    Continue
                end
            end
        end
        /* Judge the event type and conduct corresponding
        processes                                */
        if NextEvent is TravelMoving then
            do EventOfTravelMoving(operator) from the Agent Object
        else if NextEvent is SwapBattery then
            do EventOfSwapBattery(Clock, operator) from the Agent
              Object
        else
            do EventOfReservedSwapBattery(Clock, operator) from
              the Agent Object
        end
    end
    /* Calculate The Objective Value of the Scenario     */
    Compute the Indicators of Service Level
    Compute the AverageofObjectiveValues, which is the SampleMean
end
Compute the SampleMean and StandardErrorOfSampleMen of the
  selection
Score ← Score + SampleMean
return Score
```

Algorithm 1 Calculation of fitness for a feasible solution

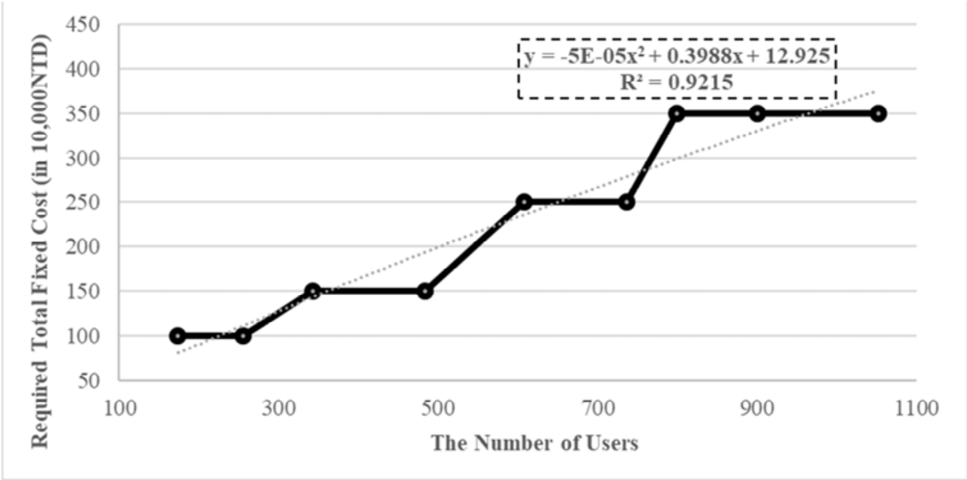

Fig. 12 Required total fixed cost to reach the upper bound of successful battery swapping percentage.

The integers next to the stars represent how many batteries are stored in the station. The value of 1 next to each station means that only one set of batteries is necessary. The percentages next to the stars indicate the percentages of users are served by the associated stations. The SDES and location optimization also provide information regarding the number of required stations to serve all users satisfactorily. This information is useful when a new market is considered. Thus, an approximate curve of the required quantity of batteries to reach the upper bound of successful battery swapping is estimated and illustrated in Fig. 12. Notably, the upper bound of successful battery swapping percentage is not always 100%. For example, if a user lives far from any candidate location and the power level of the user's battery is low when the simulation starts, a successful battery swapping is impossible for the user regardless of the number and location of stations. The shape of the curve is nearly linear, and it shows that for every 100 users entering the system, nearly every 500,000 NTD are required to serve them. The value 500,000 NTD also indicates the fixed cost of a charger. Thus, this insight suggests that each charger can support 100 new users in this particular case.

Sensitivity analysis on several important parameters is conducted to further validate the proposed methodology.

Total budget of fixed cost

Table 3 demonstrates the sensitivity analysis of the total budget. As shown in Table 3, a positive relationship between the budgets and the fitness score can be observed, which is a reasonable and straightforward outcome. Notably, a 1.5 million budget is sufficient for this case, and the ratio of successful swapping is up to 95.1%. Consequently, any additional budget only brings slight improvements. As Table 3 shows, the most successful battery swapping is first battery swapping. Moreover, the ratio of successful swapping can be raised from 39.3% to 95.1% if an additional 500,000 budget or equivalently a new charger can be provided. Furthermore, the average travel distance for swapping decreases by generally increasing the budget. This phenomenon is also reasonable because increasing the budget implies additional stations. The budget of 1 million is utilized as the base case for the rest of the analysis because this case still has space for improvement, thereby possibly uncovering the performance of the other parameters.

Table 3　Sensitivity analysis of total budget of fixed cost

Given Total Budget of Fixed Cost (10,000 NTD)	**50**	**100 ***	**150**	**200**	**250**	**300**
fitness score	−11719.07	−3996.09	−336.19	0.11	0.19	0.24
Ratio (%)						
The Ratio of Successful Swapping	4.6%	39.3%	95.1%	100.0%	100.0%	100.0%
First Battery Swapping	4.6%	34.0%	95.1%	99.5%	99.7%	99.4%
Second Battery Swapping	0.0%	5.3%	0.0%	0.5%	0.3%	0.6%
The Ratio of Unsuccessful Swapping	92.9%	58.1%	4.6%	0.0%	0.0%	0.0%
Average Distance (km)						
The Average Travel Distance of Successful First Battery Swapping	11.1	10.6	10.4	10.5	10.5	10.5
The Average Travel Distance of Successful Second Battery Swapping	–	10.7	–	9.9	10.1	9.7
The Average Remaining Distance of Unsuccessful Swapping	1.1	0.9	1.1	0.8	–	–
Other Indicators						
Average Additional Time For Swapping (min)	14.9	10.6	0.7	0.1	0.0	0.0
Average Additional Detour Distance (km)	–	0.93	–	0.03	0.01	0.03
Average Travel Distance For Swapping (km)	8.1	7.7	8.1	8.0	7.4	7.2
Computational Time (s)	1079.4	1701.5	2789.2	3438.4	3916.2	4602.0

*: The base case for this parameter.

–: No second or unsuccessful swapping in the case.

Threshold of power level for battery power swapping

Table 4 presents the results and related important indicators. The average number of swapping requests rises dramatically given a high threshold and results in a poor service level (Table 4). This situation is logical because when the threshold becomes high, the user will want to swap a battery frequently. However, with an unchanged charging performance, the system can hardly satisfy such large number of swapping requests, thereby causing the service quality of the system to decrease. Table 4 shows that a roughly negative correlation exists between the threshold and average travel distance for swapping.

Table 4　Sensitivity Analysis of threshold of power level for battery swapping

The Given Minimum Threshold of Power Level for Battery Swapping (%)	**20.0**	**30.0**	**40.0 ***	**50.0**	**60.0**	**70.0**
fitness score	0.9	−73.5	−3996.1	−34427.1	−64229.6	−81872.1
Ratio (%)						
The Ratio of Successful Swapping	100.0%	92.5%	39.3%	5.4%	4.2%	13.9%
First Battery Swapping	100.0%	92.5%	34.0%	5.4%	4.1%	13.7%
Second Battery Swapping	0.0%	0.0%	5.3%	0.0%	0.2%	0.2%
The Ratio of Unsuccessful Swapping	0.0%	6.6%	58.1%	93.2%	94.6%	85.2%
Average Distance (km)						
The Average Travel Distance of Successful First Battery Swapping	15.2	12.2	10.6	8.8	7.9	10.5
The Average Travel Distance of Successful Second Battery Swapping	−	−	10.7	−	9.3	7.6
The Average Remaining Distance of Unsuccessful Swapping	−	0.8	0.9	1.7	2.2	2.5
Other Indicators						
Total Number of Swapping Requests	8.4	44.6	125.9	227.1	331.7	453.2
Average Additional Time For Swapping (min)	0.0	1.0	10.6	14.9	18.1	16.2
Average Additional Detour Distance (km)	−	−	0.93	−	2.15	1.93
Average Travel Distance For Swapping (km)	12.1	8.5	7.7	6.0	8.2	7.9
Computational Time (s)	1787.4	1669.8	1701.5	2228.4	3072.8	3424.4

* The base case for this parameter.

−: No second or unsuccessful swapping in the case.

Power consumption rate of batteries

Table 5 lists the outcome of the sensitivity analysis of the power consumption rate of batteries. As predicted, the total number of swapping requests increases with a high power consumption rate (Table 5). The results also demonstrate that the power consumption rate for electric scooters plays an important role in enhancing the service level for the entire system. If this factor can be promoted to 0.5% every second, which is half the value of the present rate, the ratio of successful battery swapping can even reach 97.1%.

Table 5 Sensitivity analysis of power consumption rate

The Given Power Consumption Rate of Batteries (%/s)	*0.25*	*0.50*	*1.00**	*1.50*	*2.00*
fitness score	0.8	–86.7	–3996.1	–10035.0	–16823.3
Ratio (%)					
The Ratio of Successful Swapping	100.0%	97.1%	39.3%	16.3%	4.8%
First Battery Swapping	99.3%	97.1%	34.0%	13.5%	4.2%
Second Battery Swapping	0.7%	0.0%	5.3%	2.8%	0.6%
The Ratio of Unsuccessful Swapping	0.0%	2.8%	58.1%	80.9%	92.8%
Average Distance (km)					
The Average Travel Distance of Successful First Battery Swapping	10.2	10.4	10.6	10.6	10.9
The Average Travel Distance of Successful Second Battery Swapping	8.5	–	10.7	10.7	10.3
The Average Remaining Distance of Unsuccessful Swapping	–	0.8	0.9	0.8	0.8
Other Indicators					
Total Times of Swapping Request	36.0	65.9	125.9	189.2	249.8
Average Additional Time For Swapping (min)	0.1	0.4	10.6	14.6	17.8
Average Additional Detour Distance (km)	0.05	–	0.93	1.22	2.15
Average Travel Distance For Swapping (km)	9.4	7.2	7.7	7.9	8.7
Computational Time (s)	2166.5	1738.2	1701.5	2387.2	2814.8

* The base case for this parameter.
－: No second or unsuccessful swapping in the case.

Charging rate of chargers in stations

Table 6 presents the result of the sensitivity analysis of charging rates. Although the increased charging rate of chargers actually has some positive impact on service level (Table 6), the efficacy is not as high as the power consumption rate. When the charging rate turns to 0.08% every second, which is nearly twice the existing rate, the ratio of successful swapping only reaches 86.4%.

Table 6　Sensitivity analysis of charging rate of chargers

The Given Charging Rate of Chargers (%/s)	0.01	0.02	0.038 *	0.08	0.16
fitness score	–5926.2	–7137.5	–3996.1	–416.6	0.2
Ratio (%)					
The Ratio of Successful Swapping	27.8%	24.6%	39.3%	86.4%	100.0%
First Battery Swapping	27.8%	24.6%	34.0%	81.8%	99.5%
Second Battery Swapping	0.0%	0.0%	5.3%	4.6%	0.5%
The Ratio of Unsuccessful Swapping	70.0%	72.5%	58.1%	12.9%	0.0%
Average Distance (km)					
The Average Travel Distance of Successful First Battery Swapping	10.6	10.5	10.6	10.5	10.5
The Average Travel Distance of Successful Second Battery Swapping	–	–	10.7	10.6	10.4
The Average Remaining Distance of Unsuccessful Swapping	0.9	1.1	0.9	0.8	–
Other Indicators					
Total Number of Swapping Requests	126.6	126.3	125.9	126.3	127.4
Average Additional Time For Swapping (min)	11.0	11.5	10.6	2.8	0.0
Average Additional Detour Distance (km)	–	–	0.93	0.52	0.01
Average Travel Distance For Swapping (km)	7.2	8.4	7.7	7.3	8.1
Computational Time (s)	1570.2	2086.9	1701.5	1886.5	1821.8

* The base case for this parameter.

–: No second or unsuccessful swapping in the case.

IV. Conclusions and future research

4.1 Conclusions

An SDES model is developed for decision making in battery swapping systems of electric scooters. The proposed SDES model is a pioneering model that simultaneously considers all relevant factors in the battery swapping of electric scooters, including the OD demand and travel paths of users, stochastic departure times at the origin, refueling in the middle of a trip, driving distance between recharges, power thresholds of refueling, stochastic initial power levels, capacitated refueling facilities, and power consumption and recharging rates. The validity and applicability of the model are demonstrated. A location problem is solved by combing the SDES model and an optimization procedure. Decreasing the threshold of the power level for battery swapping, investing on additional chargers, and improving the power consumption rate of electric scooters substantially improve the service level of the system. However, the first method requires users to change their behaviors and is not directly controlled by the operator. Possible strategies could be promoting the event to cultivate this habit or directly providing some special offers for users who swap batteries at low power levels. The latter two methods controlled by the operator aim to provide an increased budget to construct stations and improve the power efficiency of batteries. By contrast, increasing the charging rate is less promising in improving system performance.

4.2 Future work

Some directions can be further researched. First, the locations and capacity of stations are determined in a single session. In the future, multiple-period planning can be considered to provide added flexibility to operators. Second, revenue requires consideration. For example, if revenue is included, the pricing strategy, operational policies, and even the cost benefit analysis can be derived. These issues benefit operators. The proposed SDES model can serve as a foundation for these issues. Third, real-world examples can be considered to obtain more insights to the management of electric scooters adopting the battery swapping approach.

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