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Optimized allocation of scooter battery swapping station under demand uncertainty

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ABSTRACT

Appropriately allocating battery swapping stations (BSSs) encourages drivers to use battery-operated scooters (ES) for reducing air pollution. The stochastic nature of battery swapping (BS) has not been widely discussed. Also, relatively few models have been proposed to, with particular reference to the possible demand for battery swapping, optimize the BSS locations and the appropriate number of batteries provided for the users of ESs to swap depleted batteries. Hence, this study aims to develop an optimized allocation model of grid-based scooter BSS (OAMSBSS) to be used to solve the abovementioned problem.

First, using Monte Carlo simulation for problem-solving operations, along with the consideration given to the traffic flow and population distribution, the stochastic BS model used to predict the demand of stochastic BS was proposed to estimate the various possible scenarios of BSD. Each scenario involved the location decisions and the time distribution for battery swapping demand. Optimizers were adopted to optimally allocate the BSS to both satisfy the BS demand scenarios and achieve the minimal BSS construction cost. The optimized locations of BSSs are considered to not only cost lower land rentals but also help a large number of drivers faced with the problem of the demand for BS services.

1. Introduction

The energy-related emissions from vehicles account for approximately 10 % of the air pollution across Taiwan (Wang, 2007). To reduce the energy-related emissions and improve the sustainable development of cities, the concept of electric vehicles (EVs), such as battery-operated scooters (ESs), was introduced to raise public awareness of these pollution emissions for controls on the pollution of these emissions (Sayarshad, Mahmoodian, & Gao, 2020; Wang, Li, Xu, & Li, 2020). Unfortunately, the limited number of batteries and a lack of refueling facilities make it difficult to do so. This is partly because EVs take hours to charge, and partly because their EVs' deployment and penetration of the market still remains at the inception stage (Ko & Shim, 2016). Moreover, considered different from the plug-in electric vehicles, this industry has proposed a viable option to use the quick battery swapping (BS) system. The system as such can serve to quickly replace the depleted battery with a fully charged one for continue driving (Zhang, Chen, & Zhang, 2019). Several studies have been conducted to investigate the BS system and battery swapping stations (BSSs) (Mak, Rong, & Shen, 2013; Yang & Sun, 2015a). Among those scholars, Yang and Sun (2015a,2015b) proposed a model to investigate whether the locations of battery BSSs and the routing plan of EVs in relation to battery-operated driving range limitation would be simultaneously determined.

Several companies in Taiwan developed the BS system to raise public awareness of the importance of using ESs as well. For example, two Taiwanese companies, such as Gogoro and Kymco, have successfully introduced the smart ESs equipped with an efficiently changeable BS system through a computer application program (APP) installed on a smartphone to further enhance their operational efficiencies. The

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Nomenclature

List of symbols

AVDD	Average *DDi,j* in several BSD scenarios, m
ASR	Acceptable *SR, %*
CBSE	Cost of a BSF, $NTD
CC	BSS construction cost, $NTD
$CNIBM_{i,j,t,m}$	Cumulative number of insufficient batteries at *th* hour and *mth* MCS in the grid(*i,j*)
CNBSFB	Number that a BSF could equip with removable battery
CPDFL	Cumulative PDF of location of BSD
CPDFT	Cumulative PDF of time of BSD
$DD_{i,j}$	Distance that an ES in the grid(*i,j*) will drive to the nearby BSSs to swap batteries, m
$EC_{i,j}$	Cost of equipment in the grid(*i,j*), $NTD
f(x)	Math function of time needed by ESs for BS
f(y)	Math function of location of ES
grid(i,j)	The *i*th row and *j*th column of the grid
i	The index of the row in the grid
j	The index of the column in the grid
$L_{i,j}$	Decision variables indicating if BSSs will be constructed in the grid(*i,j*). *Li,j* is 1 if BSSs will be constructed in the grid(*i*, *j*) 0 otherwise.
m	Index of time
MBNBA	Maximal number that BSS can be installed in a grid(*i,j*)
$MCNIB_{i,j}$	Maximal cumulative number of insufficient batteries in the grid(*i,j*) per day
MDD	The longest distance that ES's drivers would drive to the nearby BSSs for swapping battery, m
$NBG_{i,j}$	Number of BSS in a grid(*i,j*)
$NBIB_{i,j}$	Number of BSFs in a BSS in the grid(*i,j*)
$NBS_{i,j,t,m}$	Prepared number of removable batteries at *th* hour and *mth* MCS in the grid(*i,j*)
$NECES_{si,sj,t,m}$	Number of candidate BSSs in the grid(*si, sj*) that ES drivers could choose to BS when the ESs in grid (*i,j*) at *th* hour in need of BS
$NEMIG_{i,j,m}$	Number of ESs at *mth* MCS in the grid(*i,j*)
$NETMIG_{i,j,t,m}$	Number of ESs at *th* hour and *mth* MCS in the grid(*i,j*)
$NESIBS_{i,j,t,m}$	Number of BSD at *th* hour and *mth* MCS in the grid(*i,j*)
NBPD	Number of BSD per day
NG	Number of grids
NI	Number of rows of the grid
NJ	Number of columns of the grid
NMCS	Times of MCS
$RC_{i,j}$	Land rental cost of the grid(*i,j*), ($NTD)
s	Index of MCS
si	BSS installation index of the grid row
sj	BSS installation index of the grid column
SR	Service rate that BSD can find BSSs in the range of *DDi,j*.
$URC_{i,j}$	Unit rental cost of land per two year in the grid(*i,j*), $NTD/ 3.305 m^2
WGS	Width of grid size
x	Discrete variables for estimating the time needed by ESs for BS
y	Discrete variables for estimating the location ESs

Acronyms

APP	Smartphone computer application program
BS	Battery swapping
BSS	Battery swapping station
BSD	Battery swapping demand
BSF	Battery swapping facility
EV	Electric vehicle
ES	Electric scooter
GIS	Geographic information system
GA	Genetic algorithm
MCS	Monte Carlo simulation
NTD	New Taiwanese dollar
OAMSBSS	Optimized allocation model of grid-based scooter battery swapping station
PDF	Probability density function
TS	Tabu search

drivers can swap empty batteries with fully charged ones in seconds. Meanwhile, several companies have been planning to sell more ESs and build more BSSs because a small number of BSSs would increase the “range anxiety'' and discourage the consumer demand for ESs. (Jung, Chow, Jayakrishnan, & Park, 2014; Noel & Sovacool, 2016). Besides, if a big number of BSSs are installed appropriately, this can encourage more scooter drivers to consider this alternative. There are some overlaps between the concept of a BS system and that of recharging behaviors, and so this entails the problem of how the BSS facilities could be located. This inherent problem of how the users of ESs can locate those BSS facilities can be compared to the argument of the chicken-and-egg problem (Jung et al., 2014). Take Beijing City for example, a top-down planning process was used to do so (He, Kuo, & Wu, 2016). These charging facility development mostly depends on the local settings (Mikler, 2009). Besides the possible potential locations include the workplace, shopping malls, parking lots, and the like (Xi, Sioshansi, & Marano, 2013).

This problem of facility location could also be minimized if a grid-based system is used. This system mainly consists of small sized cells. With these cells, every possible demand distribution can be modelled on a computer. Because of the relationship between the demand distributions and the supply of related facilities modelled on a computer, we could determine the optimal capacities and locations for our facilities to be placed and fulfill certain objectives simultaneously, e.g. minimizing excess supply (Noor-E-Alam, Mah, & Doucette, 2012). The maximum covering method and the p-median method are commonly adopted to deal with the facility location problem as such (Daskin, 2011). The facility related supply and demand could mainly depend on the number of the customers residing at the network nodes (Hosseini & MirHassani, 2015). Thereby, a p-median model can possibly reduce the average service distance between the demand points and the nearest facility supplied, using a given number of facilities (Ko & Shim, 2016).

The prediction process established by Shi et al. (2019) has been applied to explore the electric vehicle charging demand distribution based on the concept of population density and distribution (Shi, Pan, Wang, & Cai, 2019; Shuanglong et al., 2019. Nonetheless, the refueling demand for vehicles is generally understood as an uncertain event considered mostly associated with the traffic flow (Jung et al., 2014; Kuby & Lim, 2007). The research conducted by Miralinaghi, Lou, Keskin, Zarrinmehr, and Shabanpour (2017) is a pioneer study to look into the demand uncertainty in relation to the problem of refueling station location (Miralinaghi et al., 2017). Likelihood, the problem of demand uncertainty is mainly due to the uncertain travel range, the various driving conditions faced by drivers (Lee & Han, 2017), or the stochastic traffic flow. Besides, previous studies have demonstrated that those drivers who need to refuel their EVs generally prefer doing so near their places of residency (Kitamura & Sperling, 1987; Sperling & Kitamura, 1986). With this in mind, the problem of uncertainty such as this might also trigger the problem of uncertain battery swapping demand. So, this particular concern should be considered in the problem of the allocation of BSSs allocation (Sun, Sun, Tsang, & Whitt, 2019; Yang & Sun, 2015b).

The facility location problem could be represented in a stochastic integer programming (IP) model (Yang & Sun, 2015a). So, the BSS location problem could be expanded to consider those uncertain events under the stochastic circumstances (Zhong, Chen, & Zhou, 2015). The uncertain events were presented in the form of specific probability density functions (PDFs). Monte Carlo simulation-based approach (MCS) was conducted repeatedly through random sampling from the PDFs to resolve the stochastic location problems, such as liquefied petroleum gas station location (Yang et al., 2020) and uncapacitated hub location (Contreras, Cordeau, & Laporte, 2011). Tian et al. (2015) combined an MCS with an optimizer to better optimize the allocation of the vehicle inspection station, considering the occurrences of uncertain events (Tian, Zhou, Chu, Qiang, & Hu, 2015). Jung et al. (2014) and Mak et al. (2013) capitalized on the random itinerary and the information on traffic flow mainly to optimize the configuration of vehicle recharging stations (Jung et al., 2014; Mak et al., 2013).

To date, little efforts have been made to investigate the optimized locations of BSSs and the appropriate number of batteries provided for the users of ESs to swap batteries at these stations. Hence, this study used the grid-based scooter BSS as the main concept to propose a model for optimizing the location allocation of the BSSs. This proposed model; otherwise known as OAMSBSS (Optimized Allocation Model of Grid-Based Scooter Battery Swapping Station), was employed to not only predict a possible consumer demand for battery swapping services and further tackle the problem of demand uncertainty, i.e. the inaccurate prediction about a consumer demand for battery swapping services. In addition, the use of a grid-based (raster) model in this study was to enable those BSS companies to flexibly allocate BSSs and install them as well. Meanwhile, based on the PDFs of the estimated locations and time needed for the BSD, several scenarios of BSD were generated, using MCS. Each individual distribution scenario on demand was assumed to show not only the different locations but also the time needed to do so. Then, two optimizers, i.e. Tabu search (TS) and genetic algorithm (GA), ably allocated a set of BSS locations, and these BSS locations satisfied the different BSDs for achieving the minimal BSSs construction cost (*CC*). Meanwhile, the optimized BSS locations and the amount of batteries assigned to each BSS were visualized by means of the geographic information system (GIS) for decision making references. This OAMSBSS was validated in this small case study, and the two optimizers were compared in terms of the efficiency. The primary novelty of this study is therefore threefold:

- This study first explored the optimized design of scooter battery swap stations due to their demand uncertainty.
- This study employed a grid-based model to enable the BSS companies to have BSSs distributed more flexibly in a grid.
- TS was first adopted to solve the problem of distributing BSSs.

2. Methodology

2.1. ES, BS, and BSS

Fig. 1 shows a schematic view of a smart ES, BSS, and battery swapping facility (BSF) together with removable batteries. In most situations, the ES equipped with two removable batteries can automatically connect to the cloud database, and so this provides onboard diagnostics through a connected APP. Through this APP, the battery can response to the ES and activate a driver's smartphone. The APP could redirect the driver to some nearby BSS locations where the driver can swap batteries when the ES runs low on juice. Each BSF is able to accommodate eight batteries to be put on charge. A maximum speed and maximum driving journey of the ES usually approaches to 60 miles per hour and 100 miles per charge, respectively. With this in mind, an ES should be great for short commuting trips in urban areas.

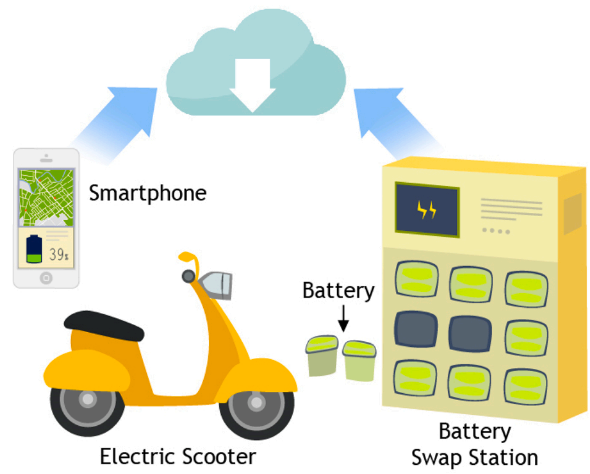

Fig. 1. Conceptual illustrations of smart electric scooters and battery swap stations.

2.2. OAMSBSS and mathematical model

As can be seen clearly from a flowchart of the OAMSBSS presented in Fig. 2, four main procedures were implemented sequentially. They mainly included the data collection and preprocessing, the prediction of stochastic BSD, the optimization process, and the display and analysis.

2.2.1. The data collection and preprocessing, and stochastic BSD prediction process

Data such as the population of scooter drivers, the scooter traffic flow, the real land rental cost, the costs of BSF, and the daily average travel distance of ESs were collected. Both the population and the land rental cost in each grid were calculated by means of Kriging interpolation. Therefore, the cumulative PDF of the population and scooter traffic flow would be obtained based the population in each grid and scooter traffic flow, respectively. In this study, the BSD locations were assumed to be proportional to the population rate, and so the cumulative PDF of location of BSD (*CPDFL*) could be obtained. Because the refueling time of gasoline-powered scooters in Taiwan is highly connected with scooter traffic flow, this study assumed that the activity of BS patterns would be the same as that of gasoline-powered scooters. In this case, the relationship between the time needed for BSD and the hourly traffic flow in this study case was proportional, and the cumulative PDF of time of BSD (*CPDFT*) could be therefore obtained.

To solve the problem of customers' BSD caused by the spatial and time uncertainty, the prediction of a stochastic BSD is proposed and shown in the green frame of Fig. 2. Based on the concept of MCS, several different BSD scenarios were repeatedly and randomly sampled from *CPDFL* and *CPDFT*. For a BSD scenario, the locations of BSD were repeatedly generated through random sampling from *CPDFL* to obtain the number of BSDs in each grid. The corresponding time of BSD generated through repeated random sampling from *CPDFT* in each grid was then obtained. More precisely, the BSD scenarios refer to location decisions and time distribution of several BSDs. A scenario generation could be regarded as an MCS, and implementing sufficient scenarios based on MCS could help reduce the custom's BSD uncertainty. The number of scenarios would vary in response to how big the problem was, and so this should be tested until the constant optimized solution was obtained. In addition, this study assumed that the number of BSDs per day (*NBPD*) would never change, but the BSD appeared at different locations and time. Thus, each scenario required the same number of BSDs, and the *NBPD* was calculated according to the daily average travel distance of ESs and the number of ESs decision makers tended to sell. For instance, if decision makers have to plan to sell 716 ESs, there will be 179 BSD per day (*NBPD* = 179). Put it simply, an ES generally drives 20

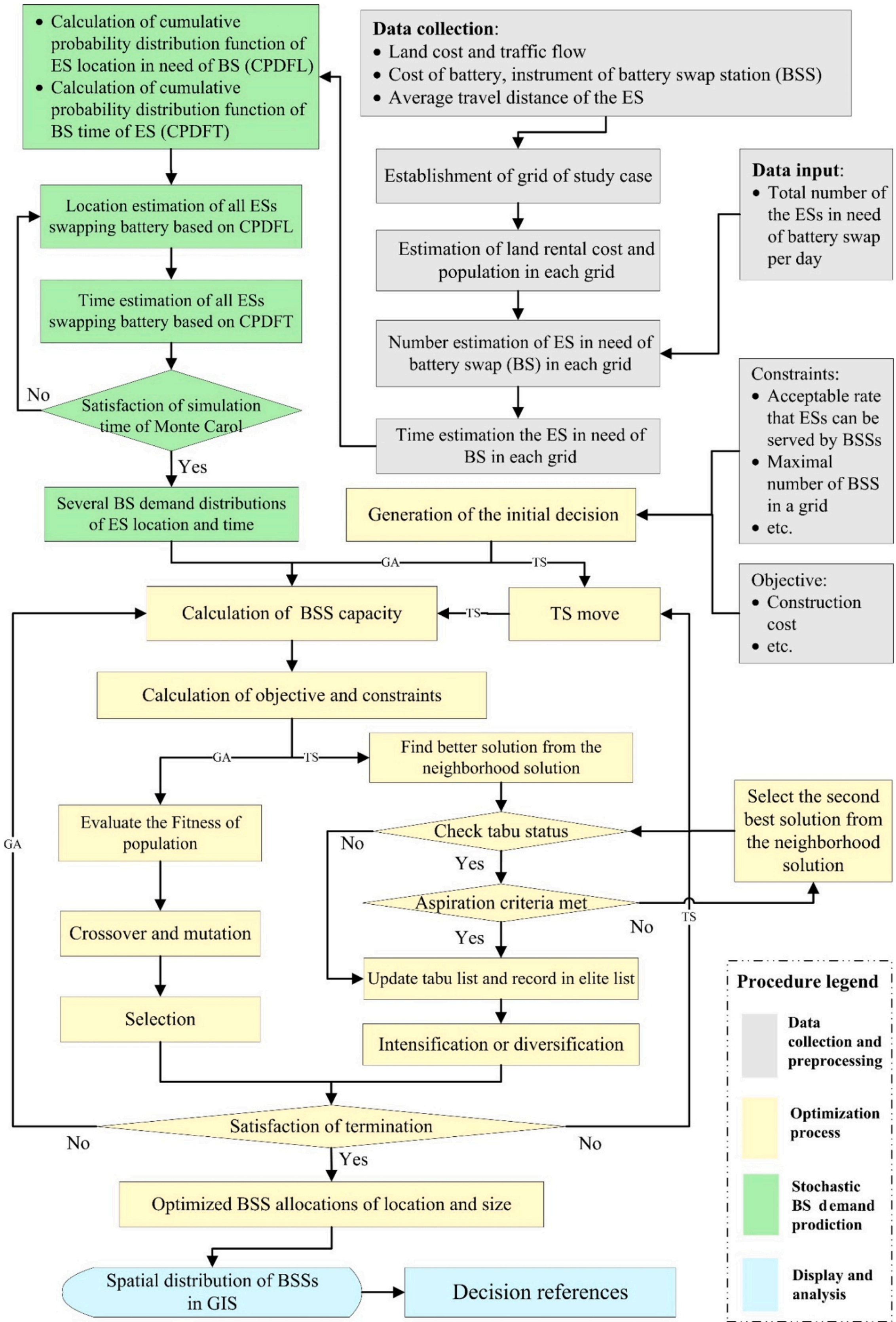

Fig. 2. A flowchart of the SMOMBA.

km per day, and the power of two batteries can supply an ES for 80 km.

Because the drivers of ESs could easily find nearby BSSs from the APP installed on their smart phones, this study could assume that these drivers would select the BSSs constructed within the shortest driving distance to perform BS (Huang, 2017). Moreover, the maximal driving distance (*MDD*) for BS to occur could be 1000 m when drivers of ES's determined to swap batteries. Still, the *MDD* could also be specified by the decision maker. That was because sometimes shorter *MDD* indicated that ES drivers could more easily do BS, and so this would help to promote ESs as well. Because an ES is generally equipped with two removable batteries, the number of removable batteries with which the BSSs should be equipped per hour was found to be at least two times the number of BSDs in the range of *MDD* during that exact hour. When an ES with empty batteries was nearby several BSSs and needed to be swapped with charged ones, the number of the removable batteries needed for the swapping as such per hour at each of the BSSs was inversely proportional to the number of the BSSs. To put it simply, when 6 ESs needed to be swapped with charged batteries due to empty ones, and they were nearby 3 BSSs within an hour, each of the BSSs should prepare 4 removable batteries for BS to occur in that hour. When a dead removable battery was placed in a BSS again, it was observed that three hours would be taken before it was fully charged.

2.2.2. The optimization process

During the optimization process, decision variable ($L_{i,j}$), otherwise known as the variables of grid, further indicated whether to install BSSs in the *i*th row and *j*th column of *grid(i,j)*, and this was considered a dummy variable. Several constraints, such as ① a maximal number of BSSs in a grid (*MBNBA*), ② *MDD*, and ③ acceptable service rate (*ASR*), could be set in the OAMSBSS. Also, both the optimizers of TS and GA have been widely applied to solve some integer programming problems (Joines, Culbreth, & King, 1996; Lokketangen & Glover, 1998), e.g. building envelope design, the BSS allocation of capacitated electric vehicles, river water quality management, and scheduling of electric buses (Chen et al., 2020; Lin, Tsai, Lin, & Yang, 2016; Yang & Sun, 2015a; Yao, Liu, Lu, & Yang, 2020). In this case, both TS and GA were performed to optimally allocate the scooter BSS locations.

TS, a heuristic approach, was firstly proposed by Glover and Languna (Glover & Laguna, 1999). It is necessary for this approach to use short term and long term memory to provide solutions. The TS optimizer mainly contains five main algorithm steps, and they consist of move, tabu list, aspiration criteria, intensification, and diversification (Lin, Sung, Chu, & Lin, 2007). The flowchart of TS is clearly presented in the middle of Fig. 2. Firstly, the initial solution (decision variable) identified was encoded as integer numbers, and thus randomly generated. The integer numbers of the variables in a grid were encoded as either 0 (the location of grid is not selected to install BSS) or 1 (the location of grid is selected to install BSS). The initial solution moves to create several neighborhood candidate solutions and to calculate the *CCs*; this type of move heavily depends on the property of problems, and so the process of either an add move or a drop move was adopted in this study. Next, the best solution was selected from those candidate solutions, and was marked as "tabu" on the tabu list (short memory). The tabu list served to keep records of the past several moves. This was to prevent cycling searches and entrapment in local optima (Laguna, 1994). Also, each local optimum in each iteration was recorded on the elite list (long memory) as well. The elite list was also updated and replaced with iterations, and the different between tabu list and elite list was solely observed in the amounts of the recorded solutions. The local optimum was checked against the aspiration criteria only when this move was tabu. The aspiration criterion was also set to accept the local optimum as a new solution to this problem when the local optimum was better than the recorded optimum. However, the local optimum was replaced by the second optimal solution among the candidate solutions if this second local optimum was not tabu. In this case, it was accepted as a new solution, and the tabu list was updated. Also, if a new solution was better than the recorded optimum, the recorded optimum was so replaced by the new solution. Above iteration continued until the maximum termination criterion was fully satisfied.

To preserve search aggressiveness and diversity, intensification and diversification strategies were implemented to do so when the iteration satisfied specific conditions. The elite list could be also applied for intensified and diversified searches, respectively (Al-Sultan & Fedjki, 1997). Diversification strategy searches unvisited regions to explore new solution spaces considered different from those solutions already obtained. When the search was not able to select a relatively optimal solution from any other optimal solutions in the elite list after a specified number of iterations, diversification was so applied by randomly perturbing all the optimal solutions in the elite list. This was to randomly generate a new solution for the next iteration. Contrary to the diversification, when the recorded optimum remains unimproved after a specified number of iterations, intensification was implemented and the TS selected the most optimal solution among these elite solutions as the new solution for next iteration. Other details of the TS search procedures were based on those derived from our previous study (Lin et al., 2016).

To base this study on the concept of the survival of the fittest, the population of GA implemented the procedures of standard evolution, which includes evaluation, crossover, and mutation, to further improve populations over generation (Mao, Chen, Wang, & Lin, 2021). Chromosomes in the population generally represent decision variables or solutions, and so they can be encoded as real numbers or substrings of binary digits or integers (Liang, Lai, Wang, & Lin, 2021; McKinney & Lin, 1994). In this study, the chromosomes were encoded in binary numbers; the code of the BSS installation was one of the following values: 0 (the location of BSS is not selected) or 1 (the location of BSS is selected). The fitness of the chromosome was expressed according to the objective values i.e. *CC*. The crossover was then conducted sequentially based on the population fitness to generate a more favorable new population. The mutation process was introduced into the population on a bit-by-bit basis at each generation to prevent the GA from converging to a local optimum. Each binary digit had an equal probability of mutating at any generation. The GA procedure continued to evolve and terminated only after reaching the maximum number of generations.

2.2.3. Display and analysis, and implement platform

On completion of the optimization process, the optimized BSS allocations and the corresponding capacity of BSSs were displayed in the output grid using GIS. This was to display the spatial distribution and size of BSSs. This grid-based display could provide other-related BSS companies with the information needed in order further to not only allocate BSSs flexibly but also to make better decisions in this regard.

2.3. Mathematical model for OAMSBSS

Eqs. (1)–(23) are the detailed math equations of the OAMSBSS; the nomenclature and definition of the symbols for each equation are shown in Nomenclature. The objectives of the OAMSBSS can be set as a quantifiable price or social cost, and the minimal *CC* was adopted for the case study to do so.

$$\text{Minimize CC} = \sum_{i=1}^{NI}\sum_{j=1}^{NJ}(RC_{i,j} + EC_{i,j}) \times L_{i,j} \tag{1}$$

$$RC_{i,j} = URC_{i,j} \times NBG_{i,j} \tag{2}$$

$$NBG_{i,j} = \left\lceil \frac{NBIB_{i,j}}{MBNBA} \right\rceil \tag{3}$$

$$NBIB_{i,j} = \left\lceil \frac{MCNIB_{i,j}}{CNBSF} \right\rceil \tag{4}$$

$$MCNIB_{i,j} = Max\{CNIBM_{i,j,m,s}\}, \forall i,j,t,m \tag{5}$$

$$CNIBM_{i,j,t,m} \in \left\{ \begin{array}{c} NBS_{i,j,t,m} \text{ If } t = 1 \\ CNIBM_{i,j,t-1,m} + NBS_{i,j,t,m} \text{ If } 2 \leq t \leq 3 \\ CNIBM_{i,j,t-1,m} + NBS_{i,j,t,m} - NBS_{i,j,t-3,m} \text{ If } 4 \leq t \leq 23 \\ 0, \text{ If } t = 24 \end{array} \right\}, \forall i,j,t,m \tag{6}$$

$$NBS_{i,j,t,m} = 2 \times NESIBS_{i,j,t,m} \tag{7}$$

$$NESIBS_{i,j,t,m} = \sum_{i=1}^{NI} \sum_{j=1}^{NJ} \frac{1}{NECES_{i,j,t,m}} \times NETMIG_{i,j,t,m} \text{ If } 0 < DD_{i,j} \leq MDD, \forall t,m \tag{8}$$

$$NECES_{i,j,t,m} = \sum_{i=1}^{NI} \sum_{j=1}^{NJ} L_{i,j} \text{ If } 0 < DD_{i,j} \leq MDD, \ \forall i,j,t,m \tag{9}$$

$$DD_{i,j} = \sqrt{(i-si)^2 + (j-sj)^2} \times WGS \tag{10}$$

$$NETMIG_{i,j,t,m} = NEMIG_{i,j,m} \times f(x), \ \forall i,j,t,m \tag{11}$$

$$CPDFT = \int_1^{24} f(x) = 1 \ x \in \{1,2,\ldots,24\} \tag{12}$$

$$NEMIG_{i,j,t} = NES \times f(y), \forall i,j,t \tag{13}$$

$$CPDFL = \int_1^{NG} f(y) = 1 \ y \in \{1,2,\ldots, \ NG\} \tag{14}$$

$$EC_{i,j} = NBIB_{i,j} \times CBSE \tag{15}$$

$$SR = \frac{1}{NMCS} \times \sum_{m}^{NMCS} \sum_{i=1}^{NI} \sum_{j=1}^{NJ} IESR_m, \ \forall i,j,m \tag{16}$$

$$AVDD = \frac{1}{NMCS} \times \frac{1}{TNES} \times \sum_{m}^{NMCS} \sum_{i}^{NI} \sum_{J}^{NJ} \sum_{si}^{NSI} \sum_{sj}^{NSJ} \times \sum_{t}^{24} \frac{NETMIG_{i,j,t,m} \times DD_{i,j}}{NECES_{si,sj,t,m}}, \forall i,j,t,m \tag{17}$$

St.

$$L_{i,j} \in \left\{ \begin{array}{c} 1, \text{ If some BSSs are installed in the grid}(i,j) \\ 0, \text{ Otherwise} \end{array} \right\}, \ \forall i,j \tag{18}$$

$$IESR_m \in \left\{ \begin{array}{c} 1, \text{ If } NESIBS_{i,j,t,m} \geq 1, \ L_{i,j} = 1, \text{and } DD_{i,j} \leq MDD \\ 0, \text{ Otherwise} \end{array} \right\}, \ \forall i,j,t,m \tag{19}$$

$$SR \geq ASR \tag{20}$$

$$NBG_{i,j} \leq MBNBA, \ \forall i,j \tag{21}$$

$$f(x) \geq 0 \tag{22}$$

$$f(y) \geq 0 \tag{23}$$

Here, *i* and *j* are indices for row and column coordinates of grid; *t* and *m* are indices for time and MCS; $RC_{i,j}$ was the land rental cost per two years for the grid(i,j). $EC_{i,j}$ represents the installation cost of BSFs. These indices *si* and *sj* indicate the position of BSSs installed in *i*th row and *j*th column of the grid, respectively. *NG* was the number of candidate BSS locations. *NI* and *NJ* are, respectively, the number of rows and columns of gird. $CNIBM_{i,j,t,m}$ is number of insufficient batteries at *t*h hour and *m*th MCS in the grid(i,j), and each removable battery must be charged at least 3 h long to be reused again. Because the BSDs per hour are variable, and this heavily depends on the traffic flow, the lowest capacity of BSSs in a grid was the maximal cumulative $CNIBM_{i,j,t,m}$ per day. The number of BSSs in a grid(i,j) ($NBG_{i,j}$) was derived from the maximal $CNIBM_{i,j,t,m}$ ($MCNIB_{i,j}$). A BSF is usually equipped with a constant number of removable batteries (*CNBFS*), and the number of BSFs in a BSS in the grid(i,j) ($NBIB_{i,j}$) is unconditional carry of $MCNIB_{i,j}$ over *CNBFS*. Because geographical limitations in an urban area (Jung et al., 2014) and a BSS usually has the effect of commercial promotion, this study assumed that a grid had an installation constraints of maximal number of BSS (*MBNBA*), and then the $NBG_{i,j}$ would be unconditional carry of $NBIB_{i,j}$ over *MBNBA*.

Because each BSD needed two removable batteries, the number of BS at *th* hour and *mth* MCS in the grid(*i,j*), $NBS_{i,j,t,m}$ was two times $NESIBS_{i,j,t,m}$. A BSS only served nearby ESs within *MDD* meters, and the number of removable batteries that each of the BSSs should prepare per hour was inversely proportional to the number of the BSSs, as shown in Eq. (8), when an BSD was nearby several BSSs. Number of BSD at *m*th MCS in the grid(i,j) ($NEMIG_{i,j,m}$) was derived from *CPDFL*, followed by number of BSD at *th* hour and *m*th MCS in the grid(i,j) ($NETMIG_{i,j,t,m}$) was derived from *CPDFT*. $DD_{i,j}$ was a distance that an BSD in the grid(i,j) would drive to nearby BSSs to swap battery. *NBPD was the total* number of BSD per day in the study area; *f(x)* is a PDF of time and defined on a time interval (1, 24); *f(y)* is a PDF of location and defined on a time interval (1, *NG*). *NMCS* is the times of MCS. After several MCS, the average $DD_{i,j}$ (*AVDD*) can be obtained. All computational code routines were handled by Visual Studio 6.0 and performed on a personal computer equipped with 12 GB of RAM and an Intel i7-8550U CPU 1.8 GHz 1.99 GHz processor.

3. Results and discussion

3.1. The case study

The region of interest was divided into two-dimensional grids to consider the problem as grid-based location problems, where each cell was made with the same dimension. The area where this study was conducted, as shown in Fig. 3, is the oldest business district located in the central district of Taichung city, Taiwan. And this area was firstly gridized by a 200-m × 200-m multiple square grid, and overlaps with road map by GIS were found. There were 39 grids ($NG = 39$) shown to be the candidate locations of BSSs. Land rent cost of all grid was estimated by Kriging interpolation. Fig. 3 shows the land rent cost of BSS installation at each grid (i,j) [$URC_{i,j}$]; some of the areas demand relatively high land rents, such as those arears located in the north the west of the study area, and so this would reduce the potential of installing BSSs. The cost of a BSF (*CBSE*) was estimated 300,000 $NTD, and the ES company would rent an area of 3.305 square meters for two years long to install a BSS. The *NBPD* in the study area was assumed to be 269. This study assumed that a BSF equipped with 8 removable batteries (*CNBSF* was 8) can provide 4 BSDs with the batteries to swap; one BSS can be equipped with a maximum of 3 BSFs in the constant rent area of 6.61 square meters, and one grid can set up to four BSSs (*MBNBA* was 4) when the width of grid size (*WGS*) is 200 m in the study case; in other words, one grid can set up to 12 BSFs when the *WGS* is 200 m. Therefore, BSS companies can flexibly configure BSS locations in the grids.

3.2. An estimation of the location decisions and the time distribution for BSDs

Fig. 4 shows the probability of the number and distribution of the time of BSDs in this case study. The probability as such could be converted into the corresponding *CPDFL* and *CPDFT*, respectively. A real random number from among 0 and 1 could be selected and directly reflected in the *CPDFL* and *CPDFT* to further estimate a possible distribution of location and time allocated to BSDs. Fig. 4(a) also shows the estimated number of BS demands presented in each grid, and the collection of all the probabilities of the results was based on the population distribution, which indicates that more BSDs would appear at the

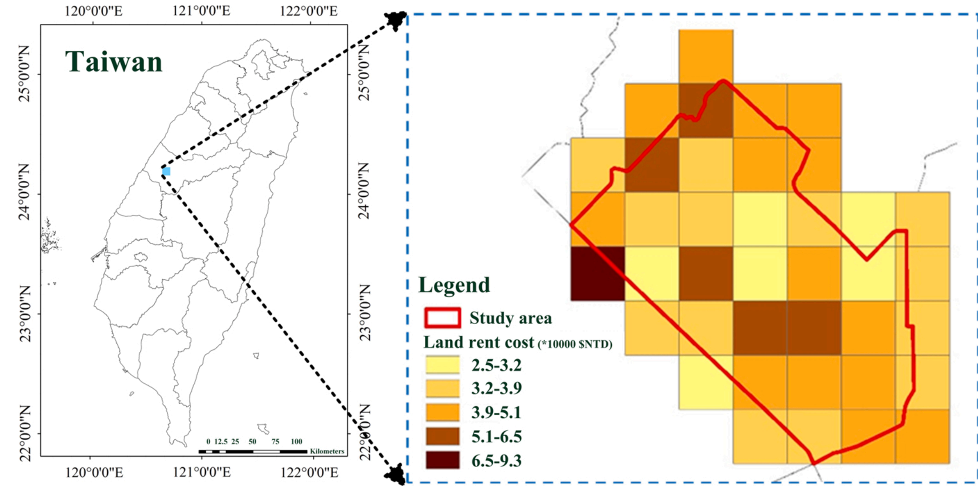

Fig. 3. Land rental of BSS installation at each grid (i,j) in the study area.

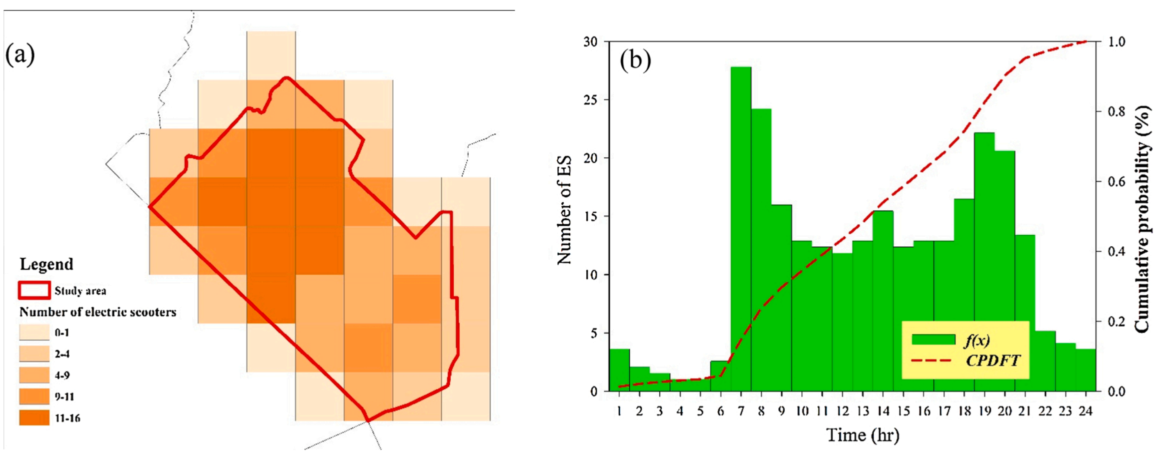

Fig. 4. (a) The number of ES in need of BS in a grid, and (b) time of ES in need of BS in a grid and the corresponding CPDFT.

north and west area. Fig. 4(a) also indicates the ratio distribution of the real population in the area where this study was conducted because the location of BSDs was assumed to be linearly proportional to the population distribution.

Fig. 4(b) shows the time and the corresponding *CPDFT* of BSD in a grid. This indicates that more than 7.4 % of the ESs (20/269) tended to swap batteries at 6:00–8:00 and 19:00–21:00. Meanwhile, more than 4% of the ES drivers in need of BS would swap batteries during 9:00–18:00. The smallest number of the ES drivers would do BS at 4:00–5:00. The largest number of the ES drivers, i.e. 28 ES drivers, would swap batteries at 7:00–8:00. This indicates that BSSs should provide 56 usable removable batteries during this period for the purpose of batter swapping. However, the removable batteries with which a BSS should be equipped, as to the $MCNIB_{i,j}$, were supposed to be larger than the member of 56. That was possibly because some removable batteries would not be chargeable, and so they could not serve to swap batteries.

In addition, Fig. 4(b) shows the time probability distribution of an ES in need of BS [$f(x)$] and the corresponding *CPDFT*. A random real number from between 0 and 1 could be directly reflected in the *CPDFT*, and then the BS time of an ES on a grid system would be calculated. Either larger spacing of vertical axis of the *CPDFT* or high value of $f(x)$ would indicate that an ES driver is highly likely to appear in the corresponding time. For example, ES drivers in need of BS would highly possibly to swap batteries at 7:00–8:00, and this time slot presented larger spacing of vertical axis of the *CPDFT*. MCS implemented the random samplings from *CPDFL* and *CPDFT*, and this simulated several different scenarios of BSDs for battery swapping stations in terms of the simulations of the uncertainty of BS. The optimized allocation of BSSs could satisfy the demand scenarios to resolve all the related uncertainty of BS.

3.3. Satisfying the BSDs through optimizing the BSS distributions

After the number of ESs and the time taken by ESs to swap batteries were estimated, the TS and GA were used to allocate optimally BSSs to satisfy the scenarios generated from the demand of BS and minimal *CC*. Such optimized distribution of the BSS locations was represented in a stochastic 0–1 IP problem. First, to verify the solutions derived from GA and TS, a small size instance with 4 × 4 grids was built, using a traditional exhaustive method. Also, the BS demand scenarios generated were sensibly known. In other words, the ES drivers were informed of the location and time for the BS services in this small size instance. In other words, the optimal solution of small size instance could be calculated. The land rental, the number of ESs in need of BS, and the time needed by ESs for BS are shown in Fig. S1(a)–(c). A total of 16 discrete decision variables ($NG = 16$) in this case were evaluated, and the solution space was comprised of 65,536 possible allocation plans. The optimized allocation of BSSs with a cost of 277,280 $NTD (*CC*) was obtained by both TS, GA, and exhaustive method. This optimized allocation is illustrated in Fig. S1(d). The result demonstrated that the methods of GA and TS could help optimize the related solutions.

In the case study, 39 discrete decision variables ($NG = 39$) were evaluated, and the solution space comprised roughly 3.5×10^{11} possible allocation plans. Also, such discrete variables made the problem of nonconvex and discontinuous (Nguyen, Reiter, & Rigo, 2014), indicating difficulty in finding the optimal allocation. Fig. 5(a) shows the optimized allocation of BSSs in the GIS, and such visual layout could better aid decision makers. The optimized allocation of BSSs with 5,744, 000 $NTD (*CC*) was obtained by both TS and GA. As expected, two grids near the central study area would be installed the BSSs because the land rental was relatively low, and the number of BSDs was relatively large, as can be seen from Fig. 4(a). Based on the results revealed, the two grids would both install 9 BSFs to satisfy 100 % of the BSDs, and the ES drivers needed to drive an average of about 519.3 m (*AVDD*) for the better BS to occur. In addition, these 9 BSFs in the grid would be mainly divided into three BSSs. This allocation satisfied the *MBNBA* constraint and caused the lowest *CC*. These above-mentioned results could validate the OAMSBSS to a greater extent. In addition, in comparison with the *CC* of 5,744,000 $NTD, when the *MDD* was 1000 m, *CC* would increase up to 6,430,000 ($NTD). In the meantime, when the *MDD* decreased by about 600 m, the BSSs would be installed in three grids with higher $URC_{i,j}$, but the ES drivers needed to drive shorter *AVDD* (about 395.2 m) to do BS. Thus, this part of the results lends support to the fact that more BSSs installation would lead to shorter driving distances for ES drivers to swap batteries.

A robustness test of TS and GA was conducted and compared to each other. As given in Fig. 5(b), the *CC* decreased when there was an increase in the number of objective calls obtained from both TS and GA, and the optimized BSSs distribution was displayed in the GIS platform. Because this study selected better *CC* in each generation of GA to display in the figure, the *CC* of the initial call objective of GA was better than that of TS. When the number of consecutively unimproved iterative solutions approached to 100, the TS implemented the diversification to escape the local better solution space, and then TS presented several downward turns to approach the best solution. By comparison, the GA performance improved repeatedly with the generation evolution, and about 3800 objective function calls could possibly reach the best solution. In other words, only 0.00001 % of all possible allocations are calculated. TS performed twice and both needed more much number of objective function calls than GA did so as further to approach the optimized allocation. This result demonstrated that GA preformed more efficiently than TS on 0–1 IP problem. This was possibly because GA was good for global search when compared with TS.

3.4. An analysis of the demand uncertainty

Both the scenario and sensitivity analyses were considered to evaluate the uncertainties of BSDs. Different BSD scenarios were generated, using several times of MCSs. As can be seen from the CC of the optimized BSS allocation shown in Fig. 6, only one scenario could be optimized for the intended allocation, and so the *CC* of the optimized BSS allocation was 4,510,000 ($NTD). Actually, the variation of only using one scenario to represent the location of BSD location and time in the grid was often very large, and this would result in different *CC*. Also, the *CC* of the optimized BSS allocations tended to increase clearly when 2 or 3 scenarios were satisfied because the installed BSSs must satisfy more different locations and time for BSD. As expected, the *CC* increased as the number of possible scenarios increased, for the locations of BS stations must satisfy as more diverse demand distributions as possible. A slight increase in the *CC* between 5 and 10 scenarios was observed, and the *CC* reached a plateau of between 5–10 and 23–35 scenarios. In this case study, the *CC* would indeed converge to a constant as the scenario size increased. The constant *CC* was 5,744,000 ($NTD) when the number of scenarios were greater than 37. This result echoes that of the effect derived from using an MCS, which would not only make the solutions converge to a stationary distribution (Geyer, 1992) but also illustrate the advantage of applying the MCS to solve the BSS allocation problem with the BS uncertainty. This MCS combined with the GA optimizer could be considered as one of the stochastic optimization methods. Also, the *CC* would never change even if the number of scenarios increased to 100 because this simply wasted a lot of computational resources. Interestingly though, except for the *CC* of 36 scenarios observed to be slightly higher than the constant *CC*, the other *CCs* of less 36 scenarios were lower than the constant *CC*; this result could be possibly attributed to the stochastic nature of traffic flow and population distribution, or could imply that other parameters, such as the number of ES and *ASR*, also

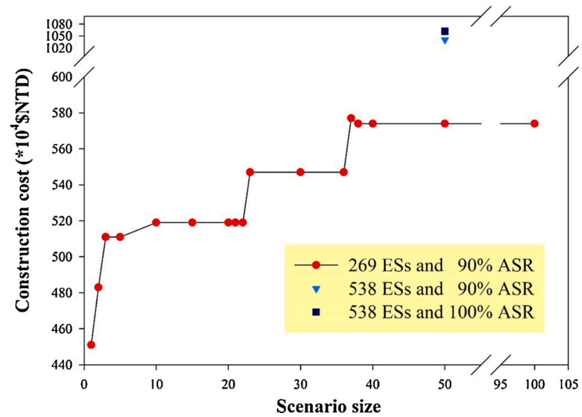

Fig. 6. Solution with different scenarios and sensitivity analyses.

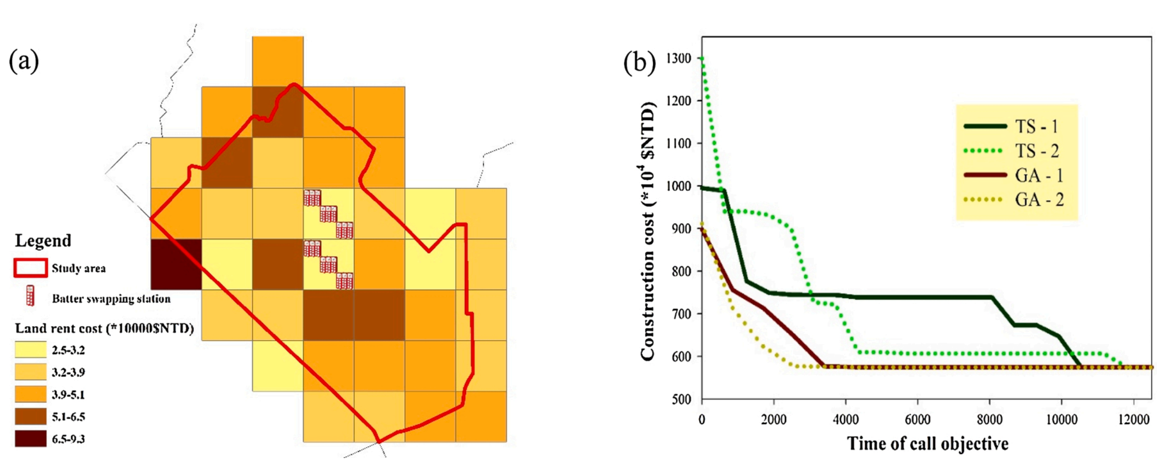

Fig. 5. (a) The optimal allocation of the battery swap station displayed in the GIS platform and (b) construction cost changes over number of objective function call of optimizer.

gave rise to the uncertainty of BS. Such variance of *CC* illustrated the uncertainty of BS events and the allocation of BSSs. In addition, this revealed that the OAMSBSS model could solve the problem of demand uncertainty in relation to the allocation of BSSs for ESs.

The *CC* would increase to 10,410,000 ($NTD), and the BSSs would be installed in the three grids when the *NBPD* increased to 538 at same *ASR*. Furthermore, the *CC* would increase to 10,620,000 ($NTD), but the BSSs would be installed in another three grids with higher $URC_{i,j}$ when the *NBPD* was 538, and *ASR* increased to be 100 %, because more $NEMIG_{i,j,m}$ appeared at the edges of the area where this study was conducted. However, this current study does not consider the influence of different grids caused by the time needed for different BS. Besides, the scope of this study is relatively limited so that the pattern generated from BS time could be assumed to be the same. For future studies to be conducted, other uncertain data should be collected, and, by doing so, more complex uncertainties could be determined.

4. Conclusions

Taiwan has the highest scooter density in the world, and the emissions derived from gasoline-powered scooters are believed to account for approximately 10 % of the air pollution in Taiwan. To promote the concept of riding electric powered scooters is to reduce air pollution to some extent. Also, the appropriate installation of BSSs is in an attempt to encourage drivers to widely use the ESs through BS. But the BS event is considered as a stochastic one, and there have been a fewer models solely proposed and established to deal with the future demand for BS with particular reference to how to determine the optimized BSS locations and the capacity needed for this to occur. Hence, based on this perspective to the subject, i.e. ESs in need of the services of BS provided by battery suppliers, this study took the possible future and uncertain BSD into account and further developed the OAMSBSS model to optimize the BSS allocations needed by the drivers of ESs. Different from those applied in previous studies, this current OAMSBSS model is a grid-based one, and this helps provide as many candidate sites as possible to be selected to install BSSs. First, the prediction of a stochastic BSD was proposed and based on the concept of MCS, the traffic flow, and population distribution. Then, the predictions about several BSD scenarios, i. e. different location and time distributions of BSD, were made. Two optimizers, referred to as TS and GA, were adopted to optimize the BS scenarios. This was to achieve the minimal *CC*. The optimized BSS locations and the capacity of each BSS were displayed in GIS through which possible decisions could be made. A small case study like this could validate the OAMSBSS. In addition, this study verified the robustness of TS and GA and implemented the uncertainty analysis of the predictions about the BSD as well.

The results showed that the same BSS allocation scheme was obtained in an optimized way by both TS and GA. The optimized BSS locations could validate the OAMSBSS because this not only avoided the relatively high but also satisfied a great deal of BSD. Specifically speaking, GA preformed more efficiently than TS in this regard, and so few objection function callings were needed. The *CC* would change significantly whenever a few of the BSD scenarios were considered. This could be possibly attributed to the stochastic nature of traffic flow and population distribution. However, the *CC* would converge to an optimized constant as the scenario size increased, and this only occurred when the number of scenarios was greater than 37, as observed in this case study. The constant *CC* would increase when there was a decrease in the number of ESs or *ASR*. Based on these aforesaid, it is hoped that game theoretical models with mutli-objectives can be possibly integrated into the OAMSBSS to better account for the market equilibrium between every and each of the private BSSs firms, government, and the users and drivers of EVs. In addition, actually only a few studies have been conducted to solve the problem of BSS allocation ESs. This is mainly because the promotion of increased awareness of ESs is not concentrated, and cars are generally regarded as the main transportation in some cities. Most of the time, ESs could be gradually promoted as means of transportation in the metropolitan areas. Simply stated, the ESs are particularly able to move quickly in the crowed metropolitan areas, and so the proposed OAMSBSS model could be used widely. In addition, when compared with ESs, in the crowed metropolitan areas, the number of electric cars is relatively small, and the car's driving mileage is longer. Also, the power station used and intended primarily for cars normally requires a larger land area, and so this is not easy to be installed arbitrarily. These conditions can possibly be the contributing factors in the problem of small solution space for the allocation of power stations intended and used primarily for cars. In other words, the problem of allocating power stations primarily intended and used for cars is easier to be solved than that associated with ESs. Finally, the results obtained from the study also highlights the particularity and value of the OAMSBSS model proposed by this study.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.scs.2021.102963.

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