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Department of Transportation and Communication Management Science

Master Thesis

The Multi-Objective Optimization of Battery Swapping Stations for Electric Scooters: Using the Artificial Neural Network Model for Demand Prediction

電動機車電池交換站多目標最佳化之研究 -以類神經網路建立需求預測模型

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電動機車電池交換站多目標最佳化之研究-以類神經網路建立需求預測模型

The Multi-Objective Optimization of Battery Swapping Stations for Electric Scooters: Using the Artificial Neural Network Model for Demand Prediction

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ABSTRACT

During the past half-century, people utilize fossil fuels as the main activation power of transport vehicles. The large amount of Greenhouse gases (GHG) emitted exacerbates the problems of global warming and climate change. Therefore, in order to create a green transportation environment with a goal of sustainable development, the development of electric vehicles that are eco-friendlier has become unanimous for all countries in the world. Compared with fuel vehicles, electric vehicles will not emit GHGs when driving, have better energy conversion efficiency and produce more diverse power sources.

Pursuant to the statistics of the Ministry of Transportation and Communications in 2019, every 100 people in Taiwan possess 93.1 scooters. In other words, the most popular private vehicle in Taiwan is the scooter. Thus, this study aims at electric scooters (ESs) as the research target. Although ESs can benefit the environment, the government confronts a huge challenge to popularize ESs. The major reason is that ESs cannot afford long-distance driving. Therefore, charging facilities are crucial. The coverage of charging facilities plays a key role for consumers to purchase ESs. Nowadays, the mainstream charging facilities on the market are divided into battery swapping facilities and recharging facilities. However, battery swapping facility will be the primary direction for the development of ESs in the future. Hence, this study discusses the optimization of the location and facility allocation of battery swapping stations while satisfying the various needs of both commercial operators and consumers.

This study builds a multi-objective optimization model to maximize the usage amount of facilities and demand coverage of users. We will optimize the location and facilities allocation with two different objectives while limiting several fixed budgets. This study

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considers various factors affecting facility usage rate (e.g., population, location characteristics, traffic status) as input variables for predicting, and uses Artificial Neural Network (ANN) to build the prediction model. In addition, the results and analysis of the two extension models under different realistic conditions will be discussed. The empirical study results indicate that: (1) Proposed ANN model is 90% accurate in predicting facility usage rate, (2) under loose budget constraints, proposed optimization model will easily incorporate too many locations with low usage rate to meet higher demand coverage, and (3) a station located in a street corner, distributor or high level of traffic status area will have a more significant positive impact on facility usage rate, while in an alley or roadside will have a more significant negative impact. The results of this study can provide a basis for the government or commercial operators to predict the usage rate of facilities and optimize the site location.

Keywords: Electric scooter, Battery swapping station, Multi-objective optimization model, Artificial Neural Network

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摘要

在近半個世紀以來，人類都以化石燃料為交通運輸主要的動力來源，其大量排放的溫室氣體導致全球暖化的問題不斷加劇。因此，為了打造以永續發展為目標的綠色運輸環境，發展對環境更加友善的電動車成為世界各國一致的目標。相較於燃油車，電動車在行駛時並不會有溫室氣體的排放、能源轉換效率較高、電力來源更加多樣化。

根據交通部 2019 年統計資料顯示，在臺灣每百人中就持有 93.1 輛機車，換句話說，臺灣民眾最主要的私人運具為機車。因此，本研究以電動機車作為欲探討之研究標的。雖然電動機車能為環境帶來極大的效益，但是臺灣邁向電動機車普及化還有非常大的距離，主要受制於其續航力尚無法負擔長途行駛，因此，電力補充設施的選址更顯得重要。目前主流的電力補充設施分為電池交換站與充電站，然而，電池交換站將會是臺灣未來發展的主要方向。因此，本研究將探討，同時滿足業者與消費者需求的電池交換站位置與設施規劃之最佳化。

本研究建構一多目標最佳化模型，以最大化電池交換站之設施使用量、消費者需求覆蓋率，在多種預算的限制下，同時以兩個不同的目標優化電池交換站的選址與設施規劃。本研究利用影響設施使用率之不同因素(如人口、區域類型、交通狀況等)作為預測之變數，並且利用類神經網路建立預測模型。在後續章節中，進一步探討不同現實條件下的兩種延伸模型之結果與分析。研究成果顯示: (1)類神經網路模型在設施使用率預測上具有 90%準確性；(2)在較寬鬆的預算限制下，模型容易納入過多設施使用率較低之站點，以滿足更高的需求覆蓋率；以及(3)設施設立在三角窗、經銷商與交通狀況較壅塞的地段對設施使用率有較顯著的正向影響，而設立在巷弄內或路側路段則會有較顯著的負向影響。本研究之研究成果可以提供政府或業者進行設施使用率預測與設點位置最佳化的決策依據。

關鍵詞: 電動機車、電池交換站、多目標最佳化模型、類神經網路

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CHAPTER 1 INTRODUCTION

1.1 Research background and motivation

In recent years, there has significant progress in human economic activities and technological development. In contrast, highly developed human activities have also brought in a lot of Greenhouse gas (GHG) emissions. These GHGs have caused serious damage to our environment, and even become the main reason of global warming and climate change. In the European Union (EU), an estimated 19 percent of all GHG emissions originate from transportation. Roughly one-half of these emissions come from private fuel vehicles. Since the beginning of the industrial revolution, CO2 emissions from burning fossil fuels have increased to 6 billion tons. One-third of this can be attributed to motor vehicles, diesel trains and aircraft (Doll and Wietschel, 2008). In Taiwan, an estimated 15 percent of all CO2 emissions originate from the transportation sector (Figure 1.1). According to the United Nations' Intergovernmental Panel on Climate Change (IPCC,2013, IPCC, 2014), most notably reduced local air quality and caused climate change due to NOx, CO2, black carbon and particulate matter emissions by fuel vehicle. Among the several solutions to reduce GHG emissions, improving vehicle fuel economy and switching from fossil fuel to lower GHG emission fuels are claimed to be two outstanding solutions (Davis et al., 2009). Therefore, electric vehicles (EVs) have attracted significant attention as they are considered as greater energy conversion efficiency and zero GHG emissions in the operation phase. Namely, in order to solve the problem of climate change and global warming, developing EV is a necessary goal.

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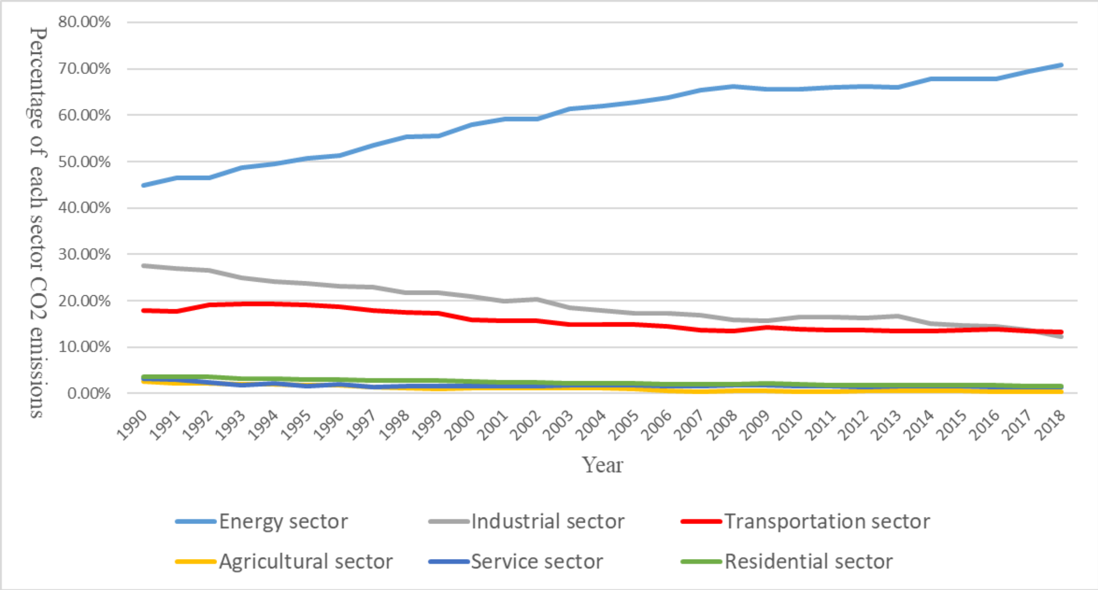

Figure 1.1 CO_2 emissions percentage of each sector in Taiwan

Source: Bureau of Energy, Ministry of Economic Affairs (1990~2018, https://www.moeaboe.gov.tw/ECW/english/home/English.aspx)

However, compared with vehicles, Taiwanese have a higher usage rate of scooters. Pursuant to the statistics of the Ministry of Transportation and Communications in 2019, there were 93.1 scooters in every 100 people in Taiwan. In other words, scooters are an indispensable part of Taiwanese. Therefore, the development of electric scooters (ESs) is a more urgent goal in Taiwan, and the ES is also the research target of this study. The government has contributed a lot to the promotion of ESs, such as using the Air Pollution Control Fund to subsidize people to purchase ESs, providing R&D program subsidies to encourage commercial operators to upgrade their technological energy, approving the "Electric Scooter Development Promotion Plan" to promote ESs. However, the promotion of ESs is still not ideal in recent years, and the gap between ESs and fuel scooters is still quite large. The main reason can be the limited availability of recharging stations (Babaee et al., 2014; Malik et al., 2016; Bradley and Frank, 2009). Furthermore, this is a chicken-and-egg issue, commercial operators do not want to invest in ESs since they do not have enough

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markets; while consumers do not want to buy ESs without sufficient recharging stations (Mitropoulos and Prevedouros, 2015). A continuing adoption of ESs by consumers and commercial operators relies heavily on the distribution of recharging facilities as low spatial coverage and inferior sitting of recharging facilities could seriously obstruct the penetration of ESs from potential consumers (Cai et al., 2014, Namdeo et al., 2014); hence, optimizing the recharging stations to satisfy commercial operators and consumers is a meaningful and urgent issue.

After Germany, the United Kingdom and France announced the prohibition against selling fuel vehicles in 2030 or 2040, Taiwan also announced that it would ban the sale of fuel scooters in 2035 and planned to subsidize establish 3,310 charging stations for ESs in the next five years. Industry Bureau officials pointed out that these charging stations will be set up at gas stations, parking lots near high-speed railway stations or railway stations and convenience stores. Due to the leading brands of ESs in Taiwan, both GOGORO and Kymco are based on battery swapping systems, and the service characteristics of battery swapping stations are more in line with the fast-paced life of modern people. Therefore, the government decided to develop battery swapping stations as the major target in the future, they estimate that the ratio of recharging stations to battery swapping stations will be 1:9. This study also aims at researching battery swapping stations, and optimize locations and allocation of battery swapping facilities in Taiwan.

In Taiwan, there are three ESs leading brands, GOGORO, e-Moving and Kymco. GOGORO is currently the most popular brand on the market, and they were the first ES manufacturer to introduce a battery swapping system in Taiwan. They greatly changed consumers' perception of ESs and attracted a large number of consumers, monopolizing most of the market share in a very short time. e-Moving used to be the first leading brand in the market when it was founded. Their products are mainly light-duty ESs and provide

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consumers with short commutes or shopping. e-Moving market share has been declining in recent years, leading them to launch mainstream heavy-duty ESs while still insisting on recharging systems as the only consideration. Kymco has been a leading brand in the fuel scooters market. Therefore, stepping into the ES market has its unique competitive advantage, which is a large number of distributors throughout the country. They can set up bases all over the country and give consumers the most convenient services. In recent years, a new ES model has been introduced, lonex. Its model can support both recharging and battery swapping systems.

An insufficient and uneconomical deployment of battery swapping stations will cause the unnecessary waste of both commercial operators and consumers, and thus the accurate prediction of optimal locating stations is necessary. Optimizing location problems for ES's battery swapping stations have not been widely studied, most are aiming at electric vehicles and recharging stations. In addition, there was less previous literature on multi-objective optimization for both supply and demand sides. Most of them were optimal problem that only considered a single objective, such as minimizing total cost or maximizing demand coverage (Nie and Ghamami 2013, Wang and Lin 2013). Research on location problems usually used a spatial interaction or gravity model to estimate real-world facilities demand based on population and distance (Kuby, et al., 2009). Several researches imposed the assumption that the potential usage amount of each recharging facility is equal since the lack of data on the actual usage of individual recharging stations (Dong and Ma, 2019). This study considered more factors (e.g., site characteristics, traffic status, income, competitors, population) affecting usage rate of facilities and then used Artificial Neural Network (ANN) to establish a prediction model for each candidate locations that have not been set any facility.

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1.2 Problem statement

In order to reduce the GHGs that will cause climate change and global warming, countries all over the world should actively develop eco-friendlier electric vehicles. However, the development of ESs in Taiwan, where scooters are the main private vehicle, is the priority. Unfortunately, although the government has been active in proposing many subsidies and incentives policy, the sales of ESs are still not ideal. According to previous literature, the primary reason is the shortage of charging stations. Nevertheless, if the demand of users is not enough, it will not attract commercial operators to invest. To solve this contradictory problem, this study uses ANN to predict the usage rate of all potential facilities setting location. Then, we construct a multi-objective optimization model with specific budget constraints to maximize the usage amount of facilities and demand coverage of users.

1.3 Research objectives

Pursuant to the stated research background and motivation, optimizing the location and allocation of battery swapping facilities with limited resources is crucial for the development of ESs and the environment. The proposed optimization model aims to maximize facility usage amount and user demand coverage while considering specific budget constraints. The objectives of this study are as follows:

1. to develop an ANN usage rate prediction model for predicting the usage rate of candidate location that has not been set any facility by using the location data that has been set facilities as training data;
2. to develop a multi-objective optimization model for the optimal battery swapping stations' locations and the number of facilities;

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3. to give the government and commercial operators advice about locating battery swapping stations for ESs.

1.4 Research flow chart

The research flow chart is illustrated in Figure 1.2. The introduction of each chapter is as follows:

1. Introduction

   This chapter discusses the issue of GHGs emissions cause environmental problems to the importance of developing ESs to replace fuel scooters in Taiwan. In order to stimulate ES's popularities, this study proposes the optimization location model of ESs battery swapping stations.

2. Literature Review

   In this chapter, we introduce the characteristics, development, market status and business model of ESs. Next, we review several location models, ANN and multi-objective optimization approaches (MOA).

3. Model development

   This study develops an ANN prediction model for predicting the facilities usage rate of candidate locations, and then we propose a multi-objective optimization model for the optimal battery swapping stations' locations and the number of facilities. The optimization model considers both commercial operators and consumers, which include the facilities usage amount and demand coverage.

4. Data collection

   We collect several realist data of battery swapping stations, which include population, income, traffic status, 112 current nodes and 111 candidate nodes to predict facility usage rate and optimize location.

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5. Results analysis

The result analysis of this study is divided into two sections: the ANN model and the optimization model. The result analysis of the ANN model includes prediction accuracy assessment and sensitivity analysis, while the optimization model includes result presentation and data analysis.

6. Conclusions and recommendations

Based on the research results in this study, we make conclusions and recommendations.

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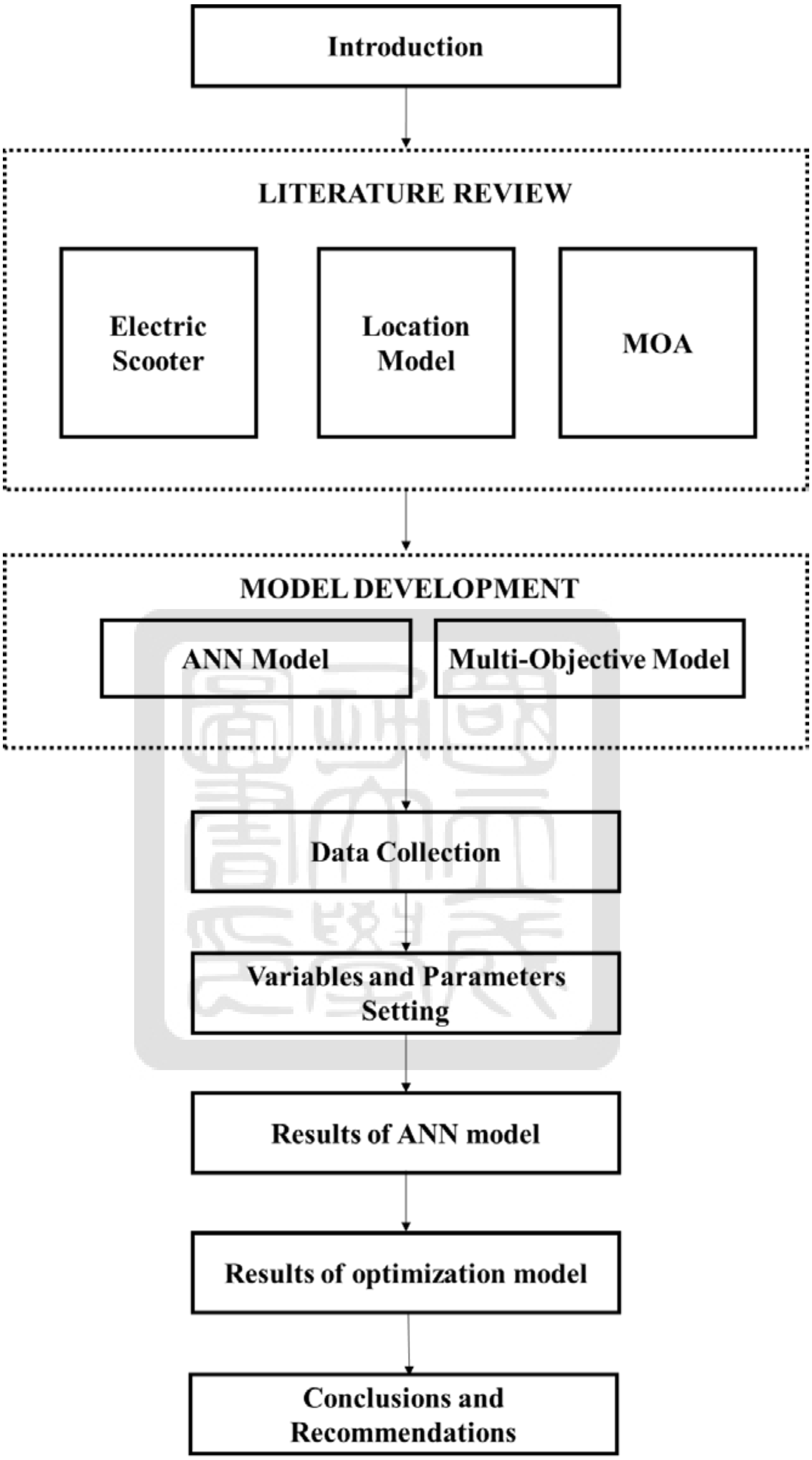

Figure 1.2 Research flow chart

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CHAPTER 2 LITERATURE REVIEW

In this chapter, we review the literature on electric scooters, charging stations, location models, ANN and multi-objective optimization approaches. This chapter is organized as follows. Section 2.1 reviews the literature on electric scooters. Section 2.2 reviews location models. Section 2.3 reviews ANN, Section 2.4 reviews the multi-objective optimization approach. Section 2.5 concludes this chapter by summarizing the reviewed researches.

2.1 Electric scooters (ES)

The definition of electric scooter (ES) is quite different in various countries. To avoid misperception for readers and the research scope of this study is Taiwan, the definition of ESs will be unified by the Taiwan standard in this study. An electric two-wheeled vehicle refers to a two-wheeled vehicle that uses electric power as a power source. Its propulsion system consists of power units and battery system. Its main function is to convert stored electrical energy into mechanical energy that drives the vehicle. Two-wheeled vehicle generally includes ESs, electric bicycles and electric-assisted bicycles (Figure 2.1). According to the regulations of Vehicle Safety Certification Center (2012), the primary distinctions between ESs and electric bicycles are maximum travel speed and vehicle weight. The maximum travel speed of electric bicycles will not exceed 25km/h and the vehicle weighs less than 40kg; otherwise, the remaining two-wheel electric vehicles are classified as ESs.

Industrial Development Bureau developed Taiwan E-scooter Standard (TES) for the sake of solving the problem of poor performance of ES in the past. The strict detecting criteria and clear classification system helping consumers safely purchase high quality and most suitable ES for them. TES is the first specification for lithium battery ESs in the world,

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including climbing ability, maximum travel speed, acceleration, endurance performance, vehicle performance, charging system safety and lithium battery safety and so on (Table 2.1). Although there were 13 testing criteria on TES, we only selected 6 crucial items for simplifying the length of the form. In multiple detection of TES, ESs were classified into 3 types, including light-duty, original light-duty and heavy-duty electric vehicles (Figure 2.1).

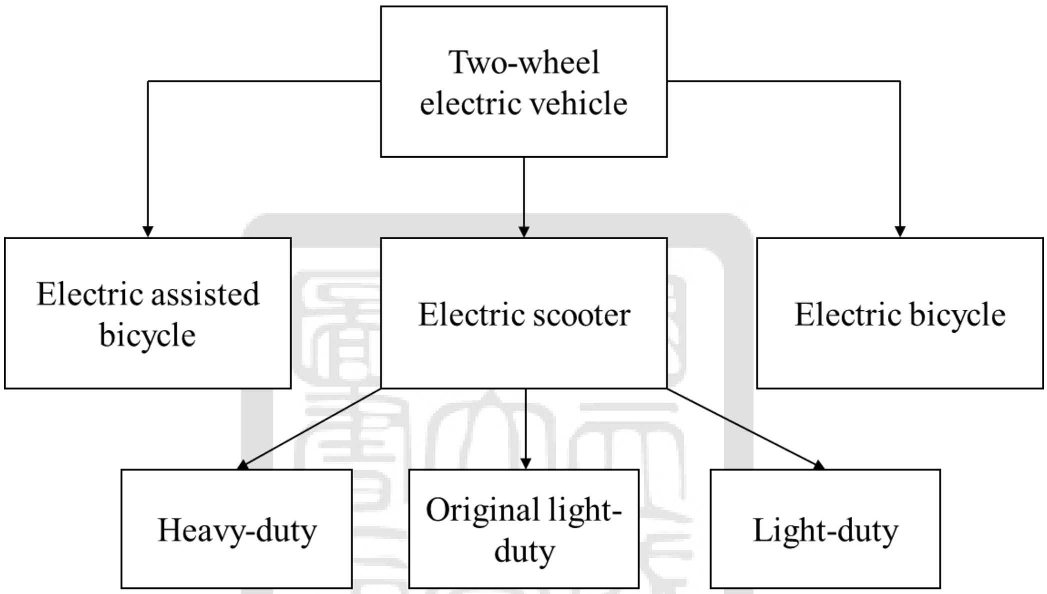

Figure 2.1 Classification of two-wheel electric vehicles

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Table 2.1 ESs classification of TES

Testing criteria	Heavy-duty	Original light-duty	Light-duty
Climbing ability (>10km/h)	30% slope	18% slope	12% slope
Maximum speed performance	>75km/h	45~75km/h	25~45km/h
Acceleration performance (0-100m)	<9s	<12s	<18s
Endurance performance (variable speed driving)	>75km	>30km	30km
Horsepower (HP)	>5HP	1.34 - 5HP	<1.34HP
License plate			

Source: Taiwan E-scooter Standard (TES)

2.1.1 Development of ESs in Taiwan

The history of ESs in Taiwan can be traced back to the first energy crisis in 1973. National Tsing Hua University and Tang Eng Iron Works company developed dozens of electric trucks as postal and telecommunications service vehicles. Their main motivation was based on energy conservation. Since then, several units have been investing in relevant research. Before 1990, most domestic research related to ESs was in a single fight situation. Until 1992, The Industrial Bureau of Ministry of Economic Affairs assumed responsibility for integrating ESs on behalf of the government. It allocated a portion of funds to support the development of ES's hardware and software equipment. The domestic ESs industry has formed a brand-new situation. There are two primary stages of ESs industry development, shown as the following:

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1. EPA promotion period (1995~2002)

Since 1995, with the goal of improving air pollution, the Environmental Protection Administration (EPA) used the Air Pollution Control Fund to subsidize people to purchase ESs. However, the subsidy was allocated to the commercial operators, so that people feeling about the government's subsidy policy are not obvious.1995 to 2003, EPA invested a total of 1.75 billion NT dollars and subsidized a total of 26,808 consumers to buy ESs. Unfortunately, EPA abrogated ESs subsidy policy in 2003 based on two factors. For one thing, sales volume was far worse than expected. For another, according to EPA's questionnaire survey for users, up to 60% of users indicated that they will not buy ESs again. Consumers had a lot of complaints about the insufficient of ES's endurance, overweight vehicle, short battery life and long recharging time. Since 2003, although EPA no longer provided purchase subsidies, international oil prices had gone up, leading to an increase in the economic benefits of using ESs; therefore, the government continued to provide R&D program subsidies to encourage commercial operators to upgrade their technological energy. The industrial vitality of ESs has not been interrupted.

2. MOEA promotion period (2009~)

In 2008, the Ministry of Economic Affairs (MOEA) aimed to promote industrial development, and announced the promotion of ESs for sailing 100,000 vehicles in four years. MOEA adopts lithium battery as the main source of ESs power to solve the problems caused by the lead-acid battery. In 2009, the Executive Yuan approved the "Electric Scooter Development Promotion Plan" which subsidized people to purchase ESs, rewarded manufacturers to expand the production scale, and subsidized commercial operators to set

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up the battery swapping stations. Moreover, MOEA pushed the target up to 160,000 domestic sales and 36,500 foreign sales within 4 years.

2.1.2 ESs market status in Taiwan

The leading brands of ESs in Taiwan including GOGORO, e-Moving, Kymco, SYM, YAMAHA. Before 2015, e-Moving occupied the large-scale majority of market share. However, GOGORO, which was launched in July 2015, has dramatically changed the competitive status of the entire ESs market. It sold nearly 4,000 ESs in just 5 months after its release (Table 2.2). This sales volume represents nearly half of the market share in the year. Nevertheless, the sales champion of the year is still e-Moving (43.2%), GOGORO temporarily ranked second (40.8%), Kymco ranked third (9.3%). Then, GOGORO quickly increased its market share in every year, and it even reached a market share of 96.3% in 2019. It can be said that it is the exclusive ESs market in Taiwan. It is notable that Kymco surpassed e-Moving in 2019 and became the second-ranked brand. Since 2009, the Executive Yuan approved the "Electric Scooter Development Promotion Plan", ESs domestic market gradually grew to 2012, and began to decline after 2012 (Figure 2.2). However, the launch of GOGORO drove the entire ES market, the annual sales volume has continuously hit an all-time high. After reviewing the development and market status of ESs in Taiwan over the years, we found that GOGORO has a great influence on the market. It can even be said that GOGORO currently represents the entire ESs market in Taiwan. Therefore, GOGORO will be the target of subsequent data collection in this study.

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Table 2.2 ES market share in Taiwan

Brand	2015		2016		2017	
	amount	%	amount	%	amount	%
Gogoro	3,894	40.8%	**12,896**	**62.5%**	**36,104**	**79.3%**
e-Moving	**4,124**	**43.2%**	4,637	22.5%	6,674	14.7%
Kymko	885	9.3%	1,093	5.3%	1,446	3.2%
SYM	33	0.3%	632	3.1%	716	1.6%
others	618	6.5%	1,370	6.6%	570	1.3%
total	9554	100%	20,628	100%	45,510	100%
	2018		2019		Accumulation	
Gogoro	**73,231**	**85.2%**	**158,498**	**91.6%**	**284,623**	**85.0%**
e-Moving	5,811	6.8%	2,769	1.6%	24,015	7.2%
Kymko	5,089	5.9%	7,960	4.6%	16,473	4.9%
SYM	985	1.1%	346	0.2%	2,712	0.8%
others	886	1.0%	3,461	2.0%	6,905	2.1%
total	86,002	100%	173,033	100%	334,728	100%

Source: Environmental Protection Administration, Executive Yuan

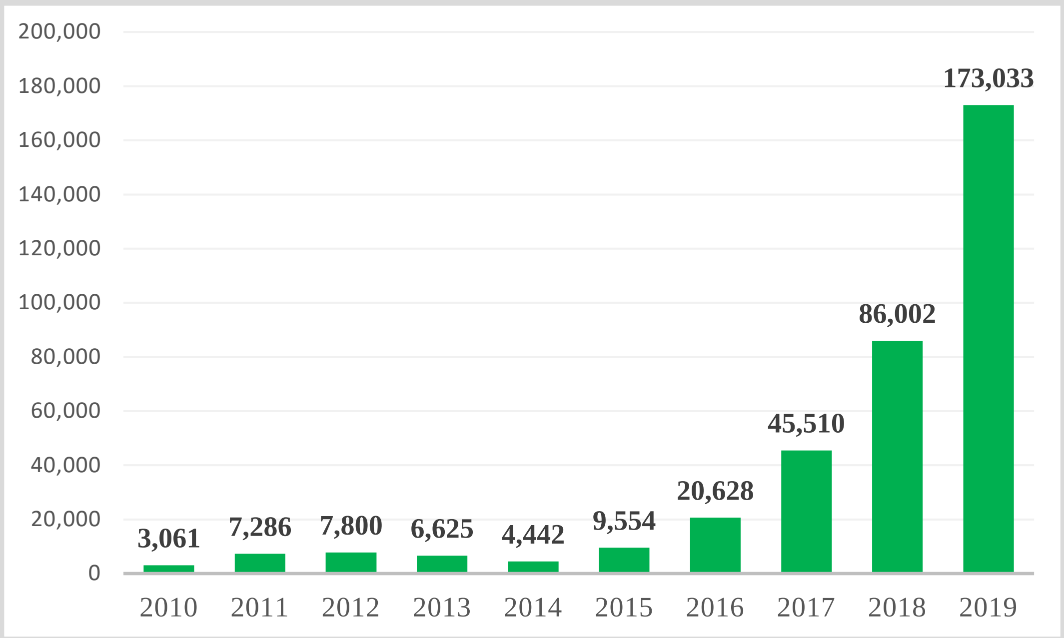

Figure 2.2 Taiwan ES total annual sales

Source: Industrial Development Bureau

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2.1.3 Business model of ESs leading brands in Taiwan

In this section, we will introduce three ESs leading brands in Taiwan, GOGORO, e-Moving and Kymco. Further, to let readers gain a greater understanding of the Taiwan ESs market, this study analyzed the business model and strategies of these brands.

1. GOGORO

Horace Luke founded GOGORO Taiwan Limited in 2011, and accessed to Taiwan ESs market in 2015 by launching their first ES, GOGORO1. The most different between traditional ESs and GOGORO is the charging mode. They developed a proprietary battery swapping system, which dramatically changed consumers perception and usage habits of ESs, and consequently attracted many consumers. So far, they have built 1,228 battery swapping stations in Taiwan. GOGORO's target customer is middle- and high-income people, trend followers, 3C merchandise enthusiasts and customers who like customized goods. GOGORO has a close relationship with its users. From the channels, maintenance, battery swapping stations and social media, GOGORO has mastered all the technologies and information. Besides the cost of purchasing vehicles, consumers should pay a monthly fee different from recharging to ride and swap batteries. By doing so, they can make it difficult for users to transfer to other brands by charging high amount of assets specificity cost. Although GOGORO has an impressive performance in the ESs market, its ultimate objective is not producing ESs. GOGORO defines themselves as an energy company rather than a scooter company, they expect to expand the new energy platform than selling scooters. Further, looking forward to attract other ESs company partners to jointly explore new markets and increase collaborative competitiveness. Therefore, GOGORO's strategy is based on the concept of patent sharing to attract other hardware operators and scooter

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manufacturers into the GOGORO ecosystem. They want to quickly occupy the market with their battery and battery swapping system in the future.

2. e-Moving

CMC launched e-Moving in 2010, and entered to Taiwan ESs market. At the beginning of the release, their major product was light-duty ES. The target customer of e-Moving was quite extensive. However, under the limitation of low endurance and low speed of its scooter, most of their consumers use it as commute, shopping and other short-distance movements. e-Moving's charging mode is based on recharging, users can directly recharge the battery at home or any roadside recharging stations. ESs has transformed from a short-distance travel tool to a transportation mode that can replace traditional fuel scooters in recently year. Along with this trend, e-Moving has also changed its sales strategy. They launched a brand-new smart ESs model in July 2019, iE125, which is a model that can compete with the normal heavy-duty scooter. This action is considered to be the attempt for entering the mainstream heavy-duty scooter market. However, although the mainstream of the current market is the battery swapping system, e-Moving still insists on recharging. They created three different recharging devices based on the various recharging times, which are slow, fast and super-fast recharging stations, and the super-fast recharging station can provide a driving distance of 78km in 10 minutes. The greatest strength of recharging stations over battery swapping stations is their fast setting and low construction cost.

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3. Kymco

Kymco has always been the industry leader of fuel scooters. However, since they entered into the ESs market in 2010, sales performance has not been as good as their performance in the fuel scooters market. The first models they launched were electric bicycles and light-duty ESs, which all can fully charge the battery and get on the road in 90 minutes, especially electric bicycles were popular among student groups because they did not need to get the driving license for riding. Moreover, in order to realize the application of the Internet of Things on the ESs, Kymco cooperated with Noodoe Corporation to develop the Internet of Vehicles system, Noodoe, in 2014. This system let users to use smart dashboard by connecting mobile application. The smart dashboard can directly display navigation, time, weather, smart compass, message notification, news, group radar function, etc. In terms of battery, the ESs of Kymco can only be recharged in the past. However, after Kymco's "Ionex Vehicle Network" comprehensive electric vehicle solution was released in March 2018, all ESs equipped with Ionex can be recharged by battery recharging and swapping. The greatest advantage of Kymco compared to other competitors is its large number of distributors across the country. They can set battery recharging and swapping stations in a suitable position more easily than others, that is, the location of their distributors. In addition to being able to recharge at home, users can also supply their battery at the recharging and swapping stations provided by Kymco's 1,600 distributors across the country. These distributors also provide battery health testing, battery usage reading, vehicle maintenance and repair services for users. In addition to the original authorized dealerships, Kymco has a total of more than 3,600 sales channels. It will also complete after-sales service bases, battery recharging and swapping stations within three years, and will expand shared batteries and shared sockets in the future.

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2.1.4 Charging stations for ESs

There are 3,255 charging stations in Taiwan, and charging stations are divided into recharging stations and battery swapping stations, there are 1,681 recharging stations and 1,574 battery swapping stations. Battery swapping stations mainly include 1,249 GOGORO, 270 Kymco and 55 ezSWAP. Various ESs brands have continually launched charging stations with exclusive specifications. Therefore, there is no uniform specification for either recharging stations or battery swapping stations. The equipment of recharging stations is relatively simple, which are consist of several sockets or external plugs similar to gas stations. The characteristics of recharging stations are long charging time, low setting cost and time, small floor area, high commonality of various ES's brands and low charging cost. Even most public recharging stations are free to use. However, battery swapping stations are different from recharging stations. The fundamental purpose of battery swapping stations is to allow users to supply their battery in the shortest time. Thus, they put the fully charged batteries in the station in advance and supplies the users to exchange the battery by their selves. The characteristics of it are short recharging time, high setting cost and time, big floor area, low commonality of various ES's brands and high recharging cost.

2.2 Location model

In this section, we discuss location problems and maximal coverage location model. First, we classify the location problems into three types by dealing with various objectives. Then, since this study calculated the demand coverage of facilities in each region, we review the maximal coverage location model that is suitable for dealing with the problem of maximizing demand coverage under limited resources.

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2.2.1 Location problems

The first study of location theory was started by Alfred Weber in 1909. The problem that Weber faced at that time was how to locate a single warehouse at the shortest distance between it and all consumers. Since 1960, location theory began to gain renewed interest and gradually developed. However, there were many types of researches on location theory, and the location problems were divided into static and deterministic, dynamic and stochastic location problems by their different considerations and research objectives. The basis of these are static and deterministic location problems, which is also been investigated in this study. The problem inputs several constant and known quantities and derives a single solution to be implemented at a point in time, such a problem is the domain that this study intends to solve. The solution will be chosen based on one of many possible criteria, as selected by the decision-maker. However, the application of static and deterministic location problems in various research objectives is also divided into several categories, namely P-median problems, covering problems and P-center problems (Owen and Daskin, 1998). Among them, covering problem is more suitable to be applied in this study. Therefore, the relevant literature and mathematical formulas of covering problem will be reviewed as follows:

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General location problems can not apply to all types of facilities. Locations that minimize the average distance or demand-weight distance may not be suitable for some facilities, such as fire stations, gas stations and ambulance. To locate these emergency service facilities, the critical issue is "coverage". The demand was covered if it can be served within a specified time or distance. Moreover, the covering problems are divided into two major segments, location set covering problem and maximal covering problem. In the location set covering problem, the objective is to minimize the cost of facility location such that a specified level of coverage is obtained. The general formulation of the location set covering problem is as follows:

Notation:

$x_j =$ 1 if a facility is allocated to site j, 0 if not

$c_j =$ fixed cost of siting a facility at node j

S = maximum acceptable service distance (or time)

N_i = set of facility sites j within acceptable distance of node i

$\left(\text{i.e.}, N_i = \{j | d_{ij} \leq S\}\right)$

Formulation:

$$\text{Min Z} = \sum_{j \in N} c_j X_j \tag{2.1}$$

$$\text{s.t.} \sum_{j \in N_i} X_j \geq 1 \qquad \forall i, \tag{2.2}$$

$$X_j \in \{0,1\} \qquad \forall j. \tag{2.3}$$

The objective function (2.1) minimizes the cost of facility location. Constraint (2.2) requires that all demands *i* have at least one facility located within the acceptable service distance. Constraint (2.3) requires integrality for the decision variables.

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The location set covering problem can examine how many facilities are needed to guarantee a certain level of coverage to all demands. However, in reality, operators need to consider whether their resources are sufficient to establish the facilities dictated by the desired level of coverage; thus, location objectives should be adjusted so that the available resources are used to provide as many demands as possible to the desired level of coverage, and this objective is the maximal covering problem (Church and ReVelle, 1974). In addition, the purpose of this study is to achieve maximum demand coverage at limited costs, which is consistent with the results of the maximal covering problem. Therefore, this study will aim to solve this problem. The maximal covering problem is to maximize the amount of demand coverage within the acceptable service distance S by locating a fixed number of facilities. The formulation of this problem requires the following additional decision variable:

Notation:

$Z_i = 1$ if node is covered, 0 if not

$h_i =$ population to be served at demand node i

$x_j =$ 1 if a facility is allocated to site j, 0 if not

$\mathrm{P} =$ the number of facilities to be located

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Formulation:

$$\text{Max Z} = \sum_{i} h_i Z_i \qquad (2.4)$$

$$\text{s.t.} \sum_{j \in N_i} X_j \geq Z_i \qquad \forall i, \qquad (2.5)$$

$$\sum_{j} X_j \leq P, \qquad (2.6)$$

$$X_j \in \{0,1\} \qquad \forall j, \qquad (2.7)$$

$$Z_j \in \{0,1\} \qquad \forall i. \qquad (2.8)$$

The objective (2.4) is to maximize the amount of demand coverage. Constraint (2.5) determines which demand nodes are covered within the acceptable service distance. Each node i can only be considered covered (with $Z_i = 1$) if there is a facility located at some site j which is within S of node i (i.e., if $X_j = 1$ for some $j \in N_i$). If no such facility is located, the right-hand side of constraint (2.5) will be zero, thus forcing Z_i to be zero. Constraint (2.6) limits the number of facilities to be located, to account for limited resources. Constraint (2.7) and (2.8) are integrality constraints for the decision variables.

2.2.2 Application of location models in charging stations

To solve the charging station location problem usually involves two steps: (1) estimating the spatial distribution of recharging demand in a research region; (2) uncovering optimal recharging stations location by formulating a mathematical programming model (Tu et al., 2016). Facility location models have already been applied to research the location problems of electric vehicles recharging stations, and the literature of electric vehicles recharging stations applying location models can be divided into three types (He et al., 2016).

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In the first type, recharging stations will locate where the recharging demand was the highest. Kameda and Mukai (2011) proposed that the recharging stations should be located at the most frequently visited regions, they used taxi probe data to simulate the traffic at the region level. Liu (2012) considered that the regional recharging demand should be estimated by the regional parking spaces and the number of gas stations. Wang et al. (2013) developed a demand model based on the energy-consuming equivalence principle and suggested that recharging stations be set in the region with relatively higher petrol sales and electricity consumption. Similarly, this study is about battery swapping stations, so our demand prediction model will estimate the demand hotspots of stations based on the usage rate of facilities. To sum up this literature, they all thought that the hotspot of the recharging demand would be served as a priority of location.

In the second type, the objective of these models is to maximize the service coverage of recharging demand. Frade et al. (2011) used a maximum coverage location model (MCLM) to optimize the demand covered with an acceptable level of service and to determine the number and capacity of the recharging stations to be installed. Wang and Wang (2010) proposed a multi-objective model to maximize population coverage and minimize the setting cost of gas stations. Xu et al. (2013) developed a GIS-based collective user utility maximization model to define the number of recharging stations needed to match the recharging demand.

In the last type, the objective is to minimize costs in various forms, such as total travel distance, time, budget and the integrated cost of all components. Chen et al. (2013) proposed a parking allocation model to determine the recharging facilities location that aimed to minimize the users' facilities access costs. Mak et al. (2013), the objective of the battery swapping facilities planning problem of EVs was to minimize the fixed costs of operating the facilities and the expected battery stations holding costs.

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2.2.3 Maximum coverage location model

This study combines the previous three types of literature into research aiming to simultaneously solve these objectives. This study develops a multi-objective model to optimize facilities usage amount, demand coverage with real data. However, we will predict the usage rate by the ANN model and each cost is derived from the research hypothesis, so that we will mainly review maximum coverage location model literature.

Nozick (2001) developed a fixed charge facility location model with coverage restrictions to minimize cost while maintaining an appropriate level of service. This research used Lagrangian heuristics with relaxing some constraints to obtain the optimal solution, and selected two networks to evaluate the heuristic. In all experiments, each location of demand serves as a potential facility location. Especially, the demand at each location was represented by the height of the vertical bars in each node, and is correlated with the population in that region.

García-Palomares et al. (2012) presented three stages of the method for optimal location in bike-sharing stations in Madrid. First, they need to know the distribution of the potential user demand. In this stage, they created a layer of points containing the population and employment associated with each building number and a layer of polygons containing the number of trips generated and attracted for each traffic region, and using these data, they calculated the kernel density maps to show the spatial distribution of the demand for bike stations. Second, developing the location model to allocate bike stations in optimal points. Once station location has been obtained, the station characteristics are described. The final stage is the analysis of station use in terms of accessibility to potential destinations. Of the location model, they used both the P-Median model and MCLM and compared their results. In the case of the same number of stations, the demand coverage of MCLM is larger than

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the P-Median model. The literature proposes that the distribution of potential user demand is related to population and employment, and that MCLM has a greater demand coverage in the study, which provides a basis for the research design of this study.

Ideally, the estimation of recharging demand should include the data of electric vehicle characteristics (i.e., type and size of EVs, and charging stations capacity) and driving characteristics (i.e., travel time, and travel distance). However, these data are difficult to obtain at the early electric vehicles’ development stage (Parker et al., 2012). Therefore, He, et al. (2016) used a weighted population in each census tract as a proxy to estimate the potential recharging demand. They selected six socio-demographic attributes to estimate demand based on the literature review and fieldwork, and the attributes are income, vehicle ownership, educational level, age, gender, and family size. After calculating the distribution of recharging demand and potential location points, they constructed a variety of models, including MCLM. In addition, they found that MCLM is more realistic in the sense, because it incorporated a budgetary constraint to limit the number of facilities to be installed and it does not require all the demand points to be covered. According to the literature, the data of vehicle characteristics and driving characteristics are difficult to obtain. Therefore, it’s reasonable to use the socio-demographic attributes to predict the usage rate of facilities, and we chose the population and income as the predicted variables.

Dong and Ma (2019) presented a method to address the optimal electric vehicles charging points location problem by using a combination of spatial statistics model and mathematical MCLM. This method consists of two steps: (1) estimating the spatial distribution of electric vehicles recharging demand from spatial statistics model; (2) calculating the maximal coverage distribution of electric vehicles recharging points from MCLM. The inputs of spatial statistics model are real-world existing recharging points location, densities of point of interest data (e.g. public transport facilities, schools,

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restaurants and offices), population characteristics and traffic flow variables in London. Further, the outputs of step 1 are estimates of spatially continuous recharging demand in the research region. In step 2, the MCLM takes estimated recharging demand as an input variable and generates the optimal deployment of recharging points location as output. Although the spatial statistics of this literature are real-world data, they still establish the key assumption that the usage of all recharging points are equivalent.

Yao et al. (2019) to optimize the spatial configuration of the fire stations, they proposed a bi-objective spatial optimization model with accounting for service coverage and access. The model aimed to locate a minimum number of facilities while ensuring each demand point can be served by at least one facility. Thus, the objectives of this model are (1) to minimize the total number of fire stations sited; (2) focus on allocation to minimize the total weight travel distance to the facilities. Concerning the estimation of spatial demand distribution, the research region is represented by a set of 1*1 km grid cell, and each grid cell thus represents a demand region with the associated fire risk estimated by the number of fire incidents per thousand population within that region.

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2.3 Artificial Neural Network (ANN)

ANN is a computational modeling tool that been found extensive acceptance in many fields for modeling complex real-world problems. “ANN may be defined as structures comprised of densely interconnected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for data processing and knowledge representation” (Hecht-Nielsen, 1998, Schalkoff, 1997). Although ANN is an abstraction of the biological, the concept of ANN is not to duplicate the operation of the biological systems but to make use of what is known about the functionality of the biological networks for solving complex problems. The attractiveness of ANN comes from originates with the outstanding information processing characteristics of the biological system such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and its capability to generalize (Jain et al., 1996).

The structure of the ANN model usually consists of an input layer, some hidden layers and an output layer (Figure 2.3). The simple processing elements are called neuron which is the basic unit to implement model calculation based on the neurons in animal species. Each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. The network uses a learning model, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights that after training, containing meaningful information whereas before training they are random and have no meaning.

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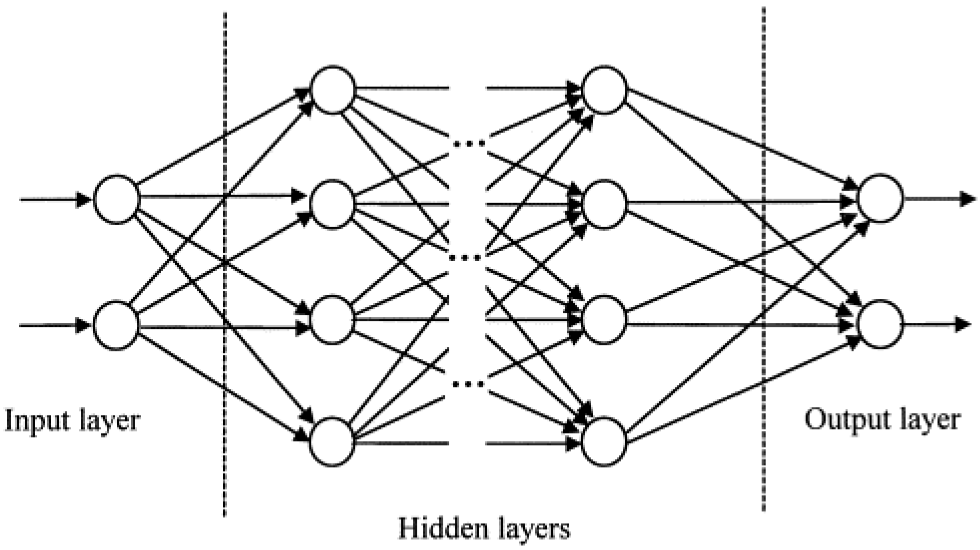

Figure 2.3 Schematic diagram of ANN model

In its simple form, the input x_i will go through the summation function and activation function to transform into output value (Figure 2.4). The summation function was formulated as equation (2.9), which is used to calculate the aggregate input from the previous layer.

Notation:

Net_j = the aggregate input to the jth neuron

x_i = the input value of the ith neuron

$w_{i,j}$ = the weight of the connection between the ith and jth neuron

θ_j = the weighted value from a bias node

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Equation:

$$Net_j = \sum_i w_{i,j} x_i + \theta_j \tag{2.9}$$

The bias node θ_j is a constant term that may help the ANN model fit best for the training data and give freedom to the model perform. The input values are multiplied by the weight coefficients, and the products are summed as a phased value Net_j. The activation functions are mathematical functions used to transform the phased value Net_j into an output value. The output value will be transformed within a certain range depended upon the activation function.

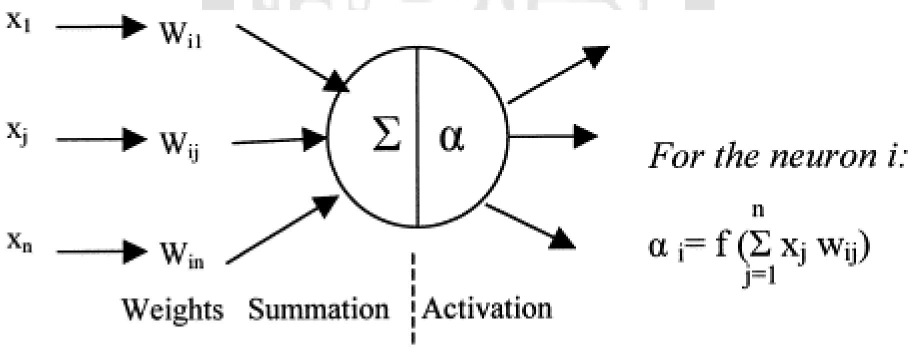

Figure 2.4 Information processing in an ANN unit

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2.4 Multi-objective optimization approach

Multi-objective optimization approach (MOA) is a method to solve problems with multiple objectives which might often conflict with each other. In the real world, most of the problems involving not only one objective. Therefore, it is not suitable to use a single objective approach to handling these problems. MOA focuses on trade-off in conflicting objectives, and was designed to help decision-makers find the most suitable non-inferior solution or compromise solution when multiple objectives conflict with each other. The multi-objective optimization model is an extension of the single objective linear programming. In the multi-objective planning, more than two objectives can be processed simultaneously, while the single objective linear programming can only process one. Thus, the optimal solution sought by single objective linear programming is a point (Max Z) and the solution sought by multi-objective planning is vector optimization (Max Z = [Z_1, Z_2…. Z_p]), is a set of points.

The methods currently used to deal with multi-objective optimization problems (MOP) can be divided into two types: the most commonly used method, classical method, is to convert the MOP into a single objective problem and then solve it; the second method, intelligent method, is to list all sub-objectives as objective function at the same time, and find all the Pareto solutions under the non-dominated relationship of each objective. Pareto solution means one feasible solution which has none of the objective functions can be improved in value without degrading some of the other objective values.

However, this study mainly reviewed the classical method. There are three popular classical methods to solve MOP by transforming to single-objective problems. Ngatchou et al. (2005) presented three methods with simple general objective functions, weighted aggregation, goal programming and ε-constraint.

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The weighted aggregation method adds the priority weight to each objective and sums to an aggregated single objective. Equation (2.10) illustrated a general form.

$$Min\ Z = \sum_{j=1}^{N} w_j f_j(x) \text{ with } w_j \geq 0 \text{ and } \sum_{j=1}^{N} w_j = 1 \tag{2.10}$$

Where the weight (w_j's) can indicate the relative importance the decision-makers attaches to objective j and will be specified for each of the k objectives a priori.

The goal programming method solved by an objective function with minimization of deviation from prespecified goals. Equation (2.11) illustrated a general form.

$$Min\ Z = \sum_{j=1}^{N} w_j \left| f_j(x) - T_j \right| \tag{2.11}$$

Where T_j represents the target or goal set by the decision-makers for the j^{th} objective function, and the w_j's now capture the priorities. As in the weighted aggregation approach, the main drawback is the need for a priori information (priorities and targets).

The ε-constraint method solved by converting some objectives to constraint with limited value ε. Equation (2.12) illustrated a general form.

$$Min\ Z = f_k(x), x \in \Omega,$$

$$s.t.\ f_i(x) \leq \varepsilon_i \text{ and } g_j(x) \leq 0, i = 1,2,\dots,N; i \neq k\ \ j = 1,2 \dots, M \tag{2.12}$$

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2.5 Summary of literature review

Pursuant to the above literature review, due to the factors of climate change and environmental protection, countries around the world regard ESs as the main development target. Especially in Taiwan, where scooters are the major private vehicle. As the 13 testing criteria of TES, ESs can clearly classify into several types. The strict detecting criteria helping consumers safely purchase high quality and most suitable ESs for them. The government released several subsidy policies and investment projects to promote ESs. They have also subsidized manufacturers to set up the charging stations. In Taiwan, ESs market share is allocated by a few leading brands. Even, the two leading brands occupied for the majority of market share in many years. This study also introduced three leading brands' business model and selling strategies. From the analysis process, we also found that although each brand developed the same type of products, their strategies and future development targets are totally different. The charging station is divided into recharging station and battery swapping station in Taiwan, and this study aim at researching battery swapping station.

After reviewing literature on location problem, we found that most of them only solved the problem of a single objective, such as maximized path-based demands that can be refueled, and did not consider the issue of cost and demand coverage. Therefore, we build a multi-objective optimization model while dealing with maximizing facilities usage amount and demand coverage. Moreover, in most of the previous literature, demand flow between the two nodes be calculated by the Gravity model, which considering a few factors, such as distance and population. We thought that the calculation of demand can consider in more factors, such as competitors, income and traffic status. Thus, we build the ANN prediction model to predict the usage rate of each battery swapping facility in different candidate setting nodes, and estimate demand coverage by calculating the population in each demand node.

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This study refers to the way the demand nodes are presented in the literature, and marks the demand of each node independently instead of marking out the service coverage. Based on the review, this study also put forward a combined with spatial statistical model and the mathematical method of MCLM, spatial statistical model of the input contains the location of the battery swapping station in the real world, nearby competitors, demographic characteristics and the traffic status.

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CHAPTER 3 RESEARCH METHODOLOGY

This study develops a multi-objective model to determine the optimal locations of ESs battery swapping stations and the number of facilities. This chapter is aimed to illustrate the model framework. Section 3.1 presented the research structure. Section 3.2 described the research assumptions Section 3.3. provide the mathematical formulation of the proposed model. Section 3.4 introduced the Artificial Neural Network (ANN) prediction model. Section 3.5 shows the research framework of proposed models. Section 3.6 summarized the model developed in this study.

3.1 Research structure

To maximize facilities usage amount and demand coverage for those battery swapping stations while setting specific budget constraints at the same time, the decision-makers have to evaluate the optimal sites among many candidate setting nodes to locate battery swapping stations. Furthermore, the most popular battery swapping system currently in Taiwan is GOGORO, so that this study considers the distribution of GOGORO types of battery swapping stations to satisfy the most users. In addition, most of the stations are located at gas stations, distributors and convenience stores. Concerning the above locations, this study will consider these types of locations as setting nodes. We collect the real-world stations and various station site characteristics data to predict facilities usage rate in each different candidate setting node. The operation process will be based on the ANN model for usage prediction.

Given the facilities usage rate of each candidate setting node, a multi-objective location model is developed to solve the facility location problem of where to locate and how many numbers of facilities need to build so that the total setting cost can be minimized.

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Furthermore, this study collects data in the Tainan area, including population, traffic status, site characteristics in each region of the Tainan area. The prediction of facilities usage rate is correlated with traffic flow and several data that we can collect from every battery swapping station's site characteristics.

3.2 Assumptions

Before developing the model, the assumptions of this study are summarized as follows:

1. The distance of demand coverage in each battery swapping station is a fixed value.
2. The budget is insufficient to meet all the demand, this study will set various budget constraints in four scenarios.
3. The candidate setting nodes for battery swapping stations, facilities setting costs and their facilities capacity are known in advance.
4. Every user will use the facility which is the nearest to their residence.
5. Even if setting up new facilities, the usage amount of the remaining facilities will not be reduced.
6. There only can set one station in the same candidate setting node.

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3.3 Proposed optimization model formulation

The notations for sets, parameters and decision variables in the proposed model are listed in Table 3.1.

Table 3.1 Notations of proposed model

Indexes	
S	The set of demand nodes, indexed by i, i =1,…,α S ∈ N
S'	The set of candidate setting nodes, index by j, j =1,…, β S' ∈ N
Parameters	
c_f	Fixed cost (NTD) of a battery swapping station, the price of a station
c_v	Variable cost (NTD) of a battery swapping station, the price of a facility
TU_j	The total usage amount at node j
Th_j	The total demand coverage at node j
P_j	Prediction usage rate at node j, average daily facility usage rate
C	The budget constraint (NTD) of total setting cost
g_i	Population to be served at demand node i
F^{max}	The maximum number of facilities at node
F^{min}	The minimum number of facilities at node
$W_{1,2}$	The weight of each objective function
β	The number of all candidate setting nodes
M	A maximum value
Decision Variables	
X_j	Total number of facilities located at node j, $X_j \geq 0$
Y_j	If the facility is located at node j, $Y_j = 1$, otherwise $Y_j = 0$

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Usage Amount

$$Max\ TU_j = \sum_{j \epsilon N} X_j P_j \tag{3.1}$$

Demand Coverage

$$Max\ Th_j = \sum_{i \in N} \sum_{j \epsilon N} g_i Y_j \tag{3.2}$$

Objective function

$$Max\ Z = W_1 TU_j + W_2 Th_j \tag{3.3}$$

Subject to

$$\sum_{j \epsilon N} Y_j \leq \beta \tag{3.4}$$

$$\sum_{j \epsilon N} (C_v X_j + C_f) Y_j \leq \bar{C} \tag{3.5}$$

$$X_j \leq M Y_j \qquad , \forall \in \ S' \tag{3.6}$$

$$Y_j \leq 1 \qquad , \forall j \in S' \tag{3.7}$$

$$F^{min} \leq X_j \leq F^{max} \qquad , \forall j \in S' \tag{3.8}$$

$$Y_j \in \{0,1\} \qquad , i \forall \in S, \forall j \in S' \tag{3.9}$$

$$C_v, C_f, F^{min}, F^{min}, P_j, X_j \geq 0 \qquad , \forall j \in S' \tag{3.10}$$

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The proposed model is linear binary integer programming, the objectives include integer variables and binary variable. In this study, the weighted aggregation method is used to simplify the original model into a single-objective planning mode and then use the optimized software Lingo to solve the problem.

Equation (3.1) is the function that maximizes the usage amount of the facilities, X_j is the total number of facilities located at node j, P_j is the prediction usage rate of node j. Equation (3.2) is the function that maximizes demand coverage of locations, which is used to calculate the target population of demand node i covered by the selected node j, g_i is the target population of node i. Equation (3.3) is the objective function that optimized two objectives, W_i is the set of two weights of each objective. Constraint (3.4) means that the number of selected nodes cannot exceed all candidate setting nodes. Constraint (3.5) requires that the total cost of facilities cannot exceed the budget constraint, C_v is variable cost and C_f is fixed cost. Constraint (3.6) ensures that unselected nodes will not setting any facility. Constraint (3.7) ensures that each candidate setting node only can set a single station. Constraint. Constraint (3.8) requires that the number of facilities cannot exceed or less than capacity limited. Constraint (3.9) is the binary constraints for the decision variables. Constraint (3.10) requires that the variables/parameters of $C_v, C_f, F^{min}, F^{min}, P_j, X_j$ are greater than or equal to zero.

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3.4 Proposed prediction model

In this study, we propose a method to predict facility usage rate using an ANN model. The reasons for choosing the model and the application of the multilayer perceptron are described in detail as follows.

3.4.1 ANN prediction model

Currently, ANNs are being used for a wide variety of tasks in many different areas. One major application area is the prediction (Sharda, 1994). There are several distinguishing features of ANNs that make them valuable and attractive for a prediction task. First, as opposed to the traditional model-based methods, ANNs are data-driven and self-adaptive methods in that there are few a priori assumptions about the models for problems under study. They learn from case and capture subtle functional relationships among the data even if the hidden relationships are unknown or hard to describe. Therefore, ANNs are suitable for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations. In this significance, ANNs can be considered as one of the multivariate nonlinear nonparametric statistical methods (White, 1989). Since it is easier to have data than to have good theoretical guesses about the underlying laws governing the systems from which data are generated, ANN with the ability to learn from experience is useful for many real problems.

Second, ANNs can generalize. After learning the data presented to them, ANNs can often correctly infer the unseen part even if the sample data contain noisy information. Third, ANNs are universal functional approximators. It has been shown that a network can approximate any continuous function to any desired accuracy. ANNs have more general and flexible functional forms than the traditional statistical methods can effectively deal with.

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Any prediction model assumes that there exists a hidden relationship between the inputs and the outputs. Frequently, traditional statistical prediction models have limitations in estimating this fundamental function due to the complexity of the real system. ANNs can be a superior alternative method to identify this function.

Finally, ANNs are nonlinear. Prediction has long been the domain of linear statistics. The traditional approached to time series prediction, assumes that the time series under study are generated from linear processes. Linear models have advantages in that they can be understood and analyzed in great detail, and they are easy to explain and implement. However, they may be inappropriate if the fundamental mechanism is nonlinear. It is unreasonable to assume a priori that a particular realization of a given time series is generated by a linear process. In fact, real-world problems are often nonlinear (Granger and Terasvirta, 1993). During the last several decades, there were many nonlinear prediction models have been developed, of course it also includes the ANN model. However, the ANN model is quite different than those nonlinear models, the ANN model is capable of performing nonlinear modeling without a priori knowledge about the relationships between input and output variables. Thus, the ANN prediction model is a more general and flexible modeling tool for prediction.

3.4.2 Multilayer perceptron

There are many types of ANN models (Figure 3.1), and the model applied in this study is a multilayer perceptron (MLP) which is one of the frequently used network structures. In general, as the complexity of a problem increases the theoretical understanding decreases and statistical methods are required. Recently, the use of MLP has been shown to be effective alternatives to more traditional statistical techniques (Schalkoff, 1992). The MLP is composed of a parallel distributed processing system that operates through interrelated

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artificial neurons to implement human thought (Feldman and Ballard, 1982). The MLP consists of a system of simple interconnected neurons, as illustrated in Figure 3.2, which is a classical learning structure for training networks with two hidden layers. The feedforward network as MLP is widely and frequently used for prediction (Golden et al., 1997). It has been shown (Hornik et al., 1989) that the MLP can be trained to approximate virtually any smooth, measurable function. Unlike other statistical methods the MLP makes no prior assumptions concerning the data distribution. It can model highly nonlinear functions and can be trained to accurately generalize when presented with new, unseen data.

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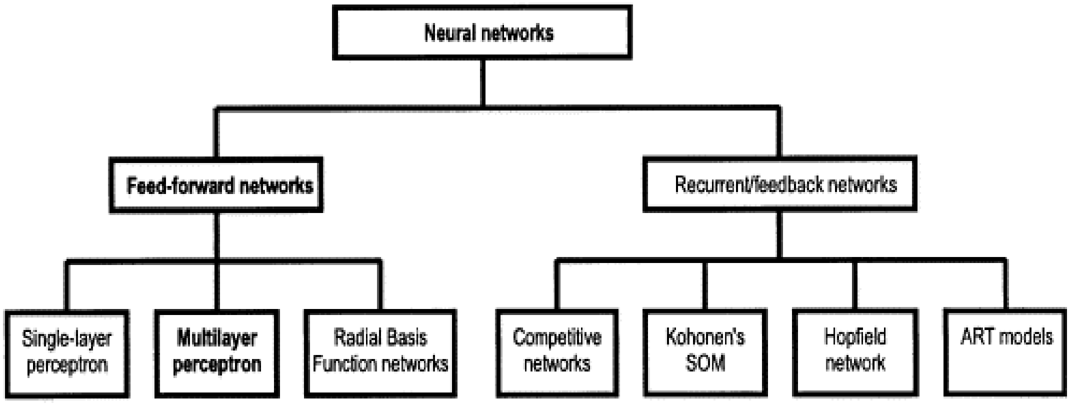

Figure 3.1 A taxonomy of ANN architectures

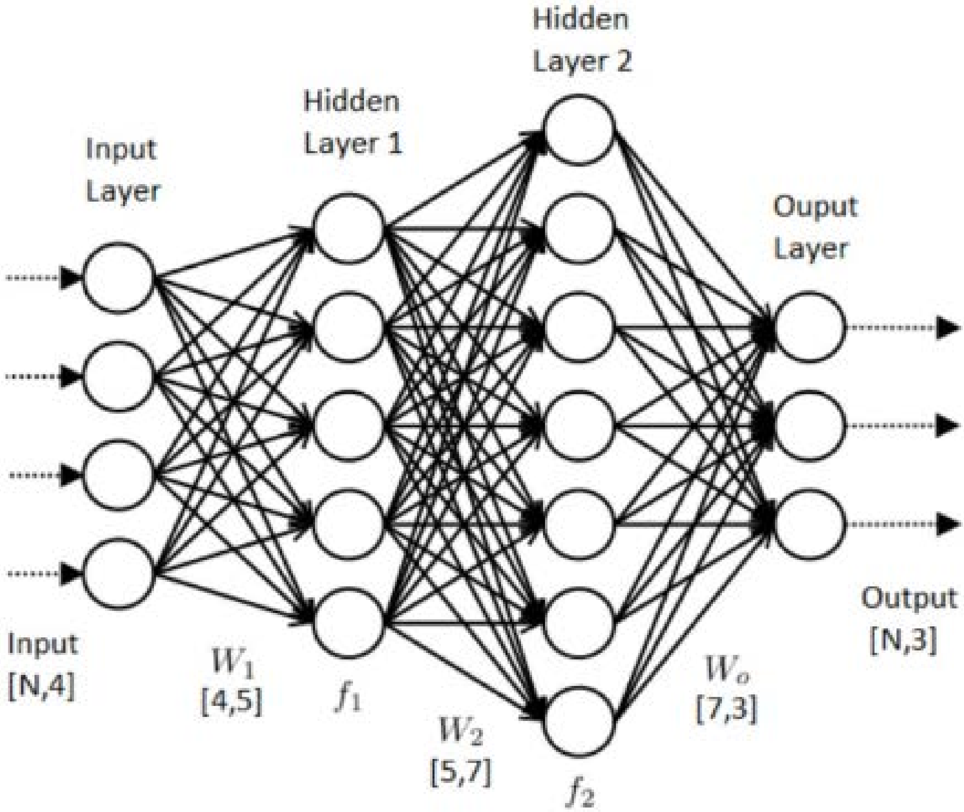

Figure 3.2 A MLP with two hidden layers

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3.5 Research framework of methodologies

In most of the previous literature, the usage amount between two nodes was calculated by the Gravity model or presented hypothetically, but we think that the estimate of usage amount can consider in more factors, therefore, this study utilizes deep learning to predict the facility usage rate of the candidate station through the realistic station data, and then the multi-objective optimization model is used to solve the optimal location and number of facilities.

In the research process, seven site variables will input into the ANN model to predict the facility usage rate of each station, and the predicted usage rate will bring into the multi-objective optimization model, the model which handles multiple data types, namely covered population, facility usage rate and setting cost. Among them, covered population collected from public government information; setting cost are several parameters set by this study, including fixed cost, variable cost and cost constraint. After the optimization operation, we will obtain the optimal location and the best number of facilities for each station (Figure 3.3).

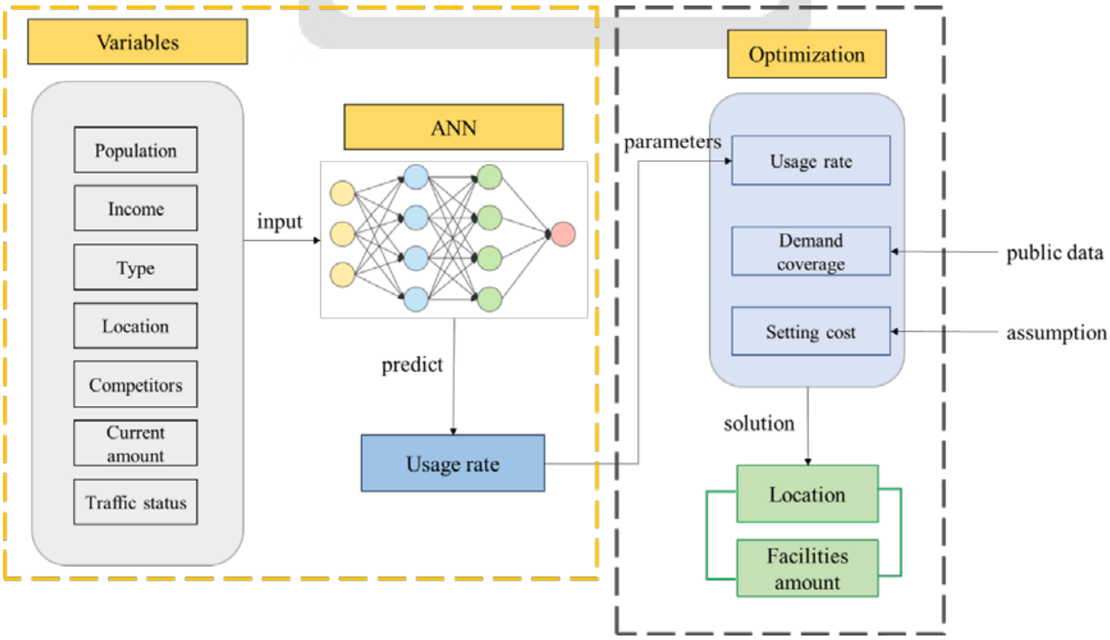

Figure 3.3 Research process

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3.6 Summary of research methodology

This chapter introduced the proposed model in this study, including the problem statement (Section 3.1), which stated three types of location characteristics; explained how to use ANN to predict the usage rate of each facility and described the evaluation criteria of demand coverage. In order to solve the problems that (1) which candidate setting node are optimal; (2) how many facilities have to been set. The research assumptions are listed in Section 3.2. Then, the mathematical formulations of the multi-objective optimization model in this study are described in Section 3.3. Section 3.4 explained why the ANN prediction model is suitable for this study; and decided multilayer perceptron as our ANN prediction model. Finally, Section 3.5 introduced the research framework of prediction model and optimization model.

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CHAPTER 4 EMPIRICAL STUDIES

The empirical studies in this chapter were conducted in Tainan City. Section 4.1 presents the data collection. Section 4.2 describes the variable and parameter setting. Section 4.3 describes the results and analysis of the ANN prediction model. Section 4.4 describes the results and analysis of the MOA model.

4.1 Data collection

This study selects Tainan City as our research scope (Figure 4.1). We consider all battery swapping stations in Tainan City as sample data to predict the usage rate of candidate nodes. The sample data include 179 GOGORO stations in Tainan City (Figure 4.2). Since this study considered gas station, distributor and convenience store as the setting types of candidate node, we further distinguished three types of these stations and found 112 current nods as our training data of the ANN model. These current nodes distribute 30 out of 37 districts in Tainan City. We collected the same proportion of candidate nodes with the ratio of distribution and types in 112 current nodes (Table 4.1), the proposal is to let their distribution and the number of each type of station are similar to current nodes; then we collected 111 candidate nodes that also distributed in 30 districts (Table 4.2). Figure 4.3 shows that the node distribution in each region, the number on the maps shows the actual number of nodes, and the color means the range amount of the node. This study also collected the population, income, type, location, competitors, current number of battery swapping station and traffic status data around all nodes as the 7 independent variables of the ANN model; and collected the usage rate of current nodes as the dependent variable of training data in the model. In section 4.2 there will be a more detailed description of these variables.

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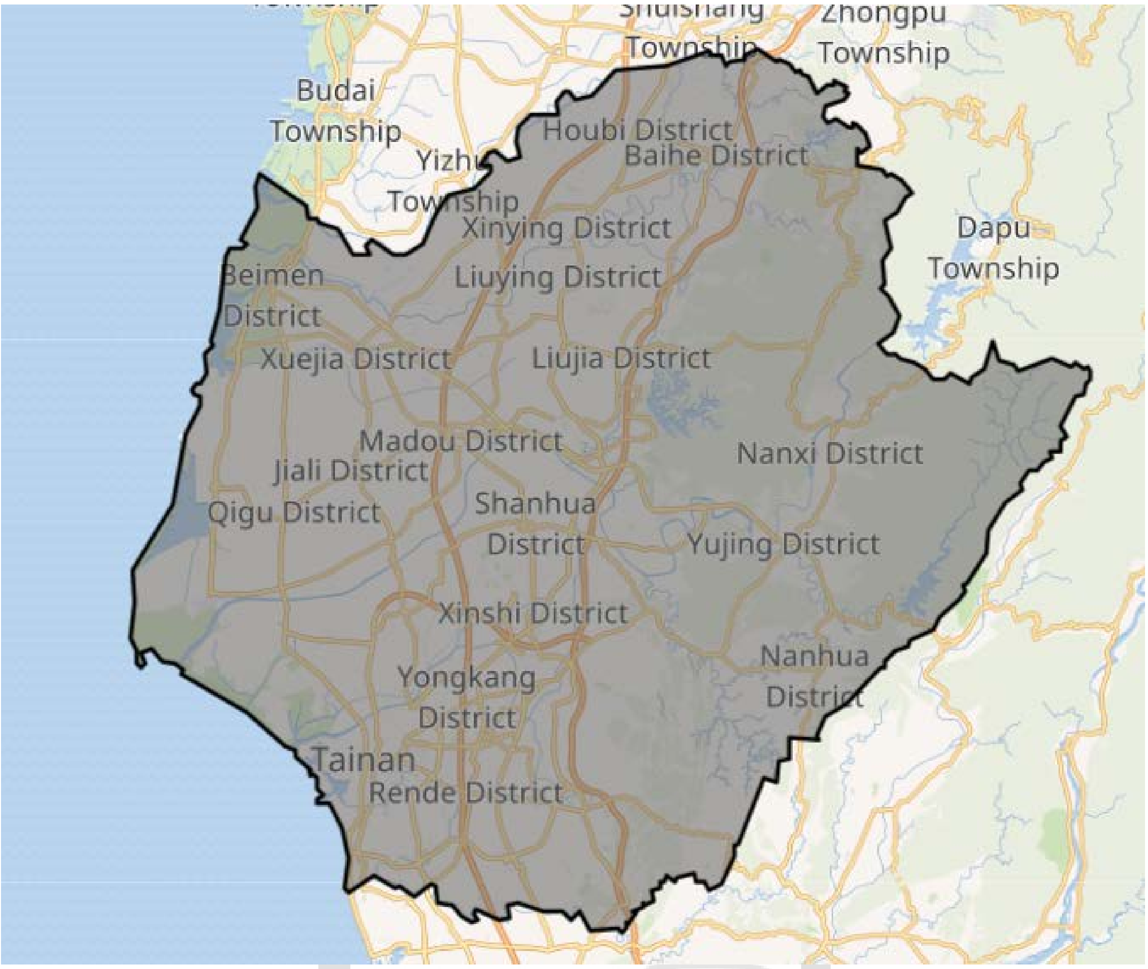

Figure 4.1 Administrative area of Tainan City

Source: Google maps

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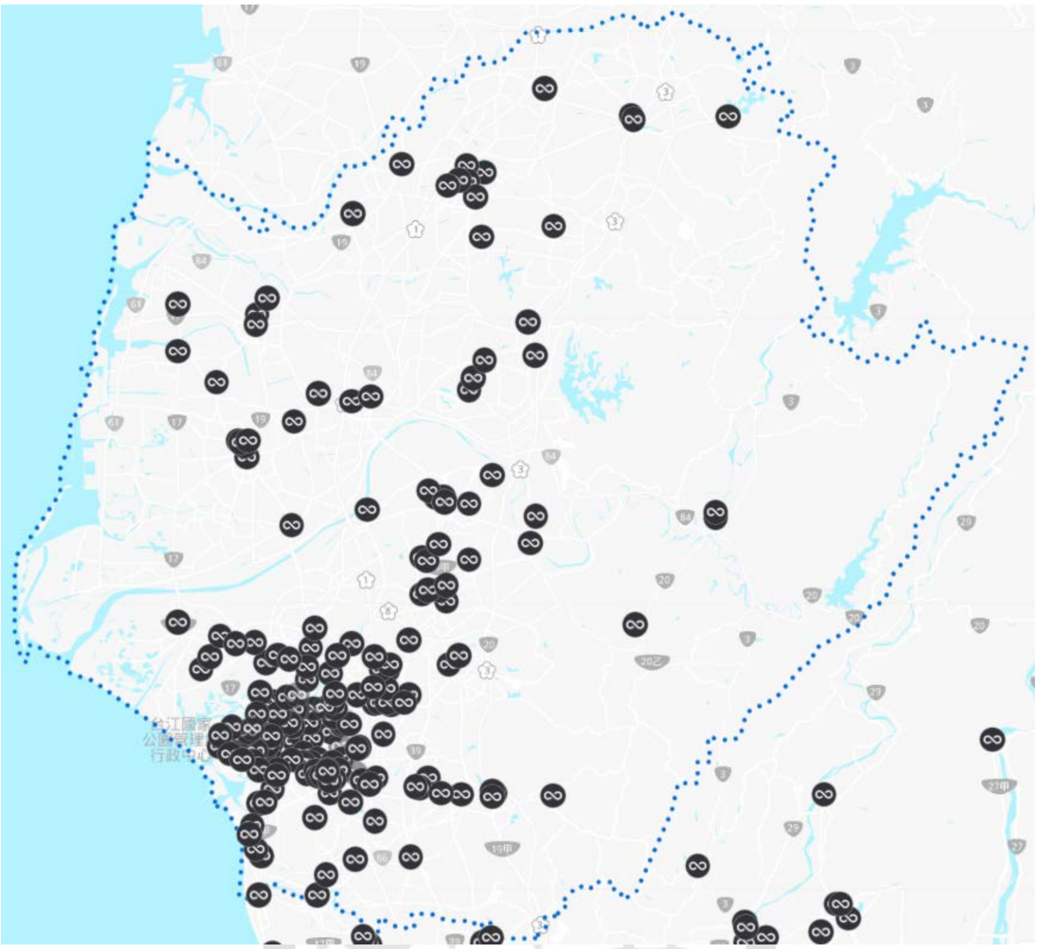

Figure 4.2 Existing stations in Tainan City

Source: GOGORO website (https://www.gogoro.com/tw/findus/)

Table 4.1 Location type of current nodes

Number	District	Gas station	Distributor	Convenience store	Total
1	**Yongkang**	1	3	9	13
2	**South**	4	1	6	11
3	**West Central**	3	1	3	7
4	**East**	4	3	3	10
5	**Annan**	3	1	5	9
6	**North**	2	3	4	9
7	**Anping**	5	1	2	8
8	**Xinshi**	3	0	3	6
9	**Shanhua**	2	1	2	5

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10	**Guiren**	2	1	1	4
11	**Guantian**	3	0	0	3
12	**Xinying**	1	1	0	2
13	**Xuejia**	2	0	0	2
14	**Jiangjun**	0	0	2	2
15	**Rende**	2	0	2	4
16	**Jiali**	0	1	1	2
17	**Yujing**	1	0	1	2
18	**Baihe**	0	0	1	1
19	**Madou**	0	0	1	1
20	**Shanshang**	1	0	0	1
21	**Xigang**	1	0	0	1
22	**Houbi**	1	0	0	1
23	**Danei**	1	0	0	1
24	**Beimen**	1	0	0	1
25	**Zuozhen**	1	0	0	1
26	**Liuying**	0	0	1	1
27	**Longqi**	1	0	0	1
28	**Guanmiao**	0	0	1	1
29	**Yanshui**	0	0	1	1
30	**Anding**	0	0	1	1
	Total	45	17	50	112

Table 4.2 Location type of candidate nodes

Number	District	Gas station	Distributor	Convenience store	Total
1	**Yongkang**	1	3	9	13
2	**South**	4	1	6	11
3	**West Central**	3	1	6	10
4	**East**	4	3	3	10
5	**Annan**	3	1	5	9
6	**North**	2	3	3	8
7	**Anping**	0	1	6	7
8	**Xinshi**	2	0	4	6
9	**Shanhua**	2	1	2	5
10	**Guiren**	2	1	1	4

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11	**Guantian**	3	0	0	3
12	**Xinying**	1	1	0	2
13	**Xuejia**	1	0	1	2
14	**Jiangjun**	1	0	1	2
15	**Rende**	2	0	0	2
16	**Jiali**	0	1	1	2
17	**Yujing**	1	0	1	2
18	**Baihe**	0	0	1	1
19	**Madou**	0	0	1	1
20	**Shanshang**	1	0	0	1
21	**Xigang**	1	0	0	1
22	**Houbi**	1	0	0	1
23	**Danei**	0	0	1	1
24	**Beimen**	0	0	1	1
25	**Zuozhen**	1	0	0	1
26	**Liuying**	0	0	1	1
27	**Longqi**	0	0	1	1
28	**Guanmiao**	0	0	1	1
29	**Yanshui**	0	0	1	1
30	**Anding**	0	0	1	1
	Total	36	17	58	111

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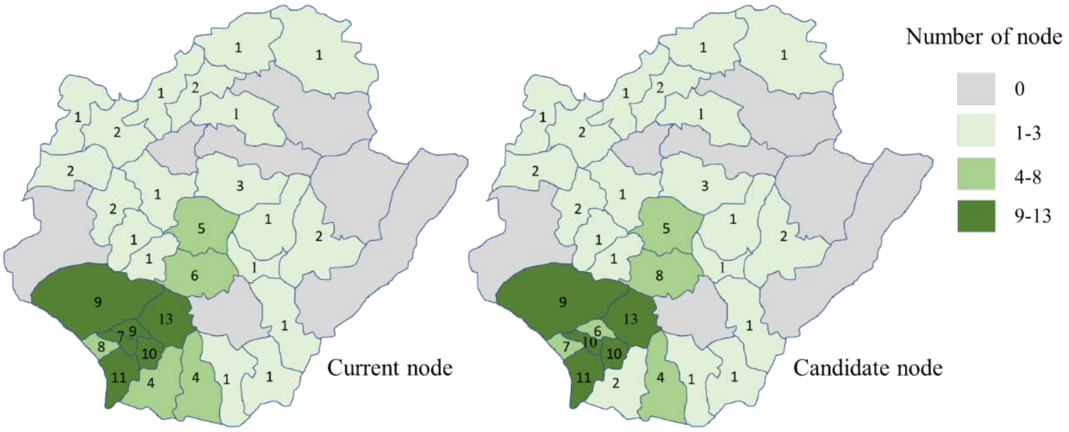

Figure 4.3 Distribution of nodes

4.2 Variables and parameters setting

The following scenarios are simulated with realistic variables and several assumed parameters, and the ANN model is applied to predict the usage rate of each candidate nodes; the proposed multiple objectives optimization model is applied to solve the battery swapping station location problem. The ANN model is constructed with Python 3.7.4, and the proposed optimization model is solved using LINGO V18.0, running at a computer with Windows 10 64-Bit OS, Intel® Core ™ i5-8250U CPU at 1.60 GHz with 8GB of RAM.

The variables used in ANN model are described as follows:

1. Population: Total population in the village of the node, source: Household registration office, Tainan city
2. Income: Total comprehensive income in the village of the node, source: Accounting and Statistics, Executive Yuan, R.O.C
3. Type: Type of the node, including gas station, convenience store, distributor.
4. Location: The location type of the node, including street corner, roadside, alley.
5. Competitors: Number of scooter stores from all other brands in the village of the node.
6. Current amount: Number of current battery swapping stations in the village of the node.

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7. Traffic status: The level of traffic status near the node, source: road condition in Google maps.

8. Usage rate: $\frac{(Total\ number\ of\ battery)-(Daily\ average\ number\ of\ fully\ battery)}{(Total\ number\ of\ battery)}$, daily average usage rate of battery for each node, this calculation method is based on the current data to estimate the approximate value, so there is a certain gap with the real facility usage rate, source: https://mowd.tw/gostation/map/battery/

The parameters used in the proposed optimization model are assumed as follows:

1. The fixed cost is set as NTD 300,000, which means that each station to be built will spend NTD 300,000.
2. The variable cost is set as NTD 25,000, which means that every battery in the station is NTD 25,000.
3. There are four kinds of cost constraints in this study, including NTD 30,000,000, 40,000,000, 50,000,000, 60,000,000, to test what changes will occur in the research results under different cost constraints.
4. The number constraints of facility in each station are set as 18 to 36, because the current facilities at existing stations is also set as the same number.

4.3 Results analysis of ANN model

In the ANN model, we utilize population, income, type, location, competitors, current amount and traffic status as the main factors that affect the facility usage rate (Figure 4.5). In the process of model construction, there are no certain criteria for the hidden layer processing unit, activation function, learning rules and other parameter settings. To obtain the most suitable network structure only if we keep training and learning repeatedly. In the selection of hidden layer units' amount, usually as the more selected nodes we get the smaller

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error and slower convergence rate; as the fewer selected nodes we get greater error and faster convergence rate; but the more than a certain number of nodes it will cause over-learning. Therefore, this study constructed the ANN model structure with the optimum accuracy after many times of training and learning the model (Table 4.3).

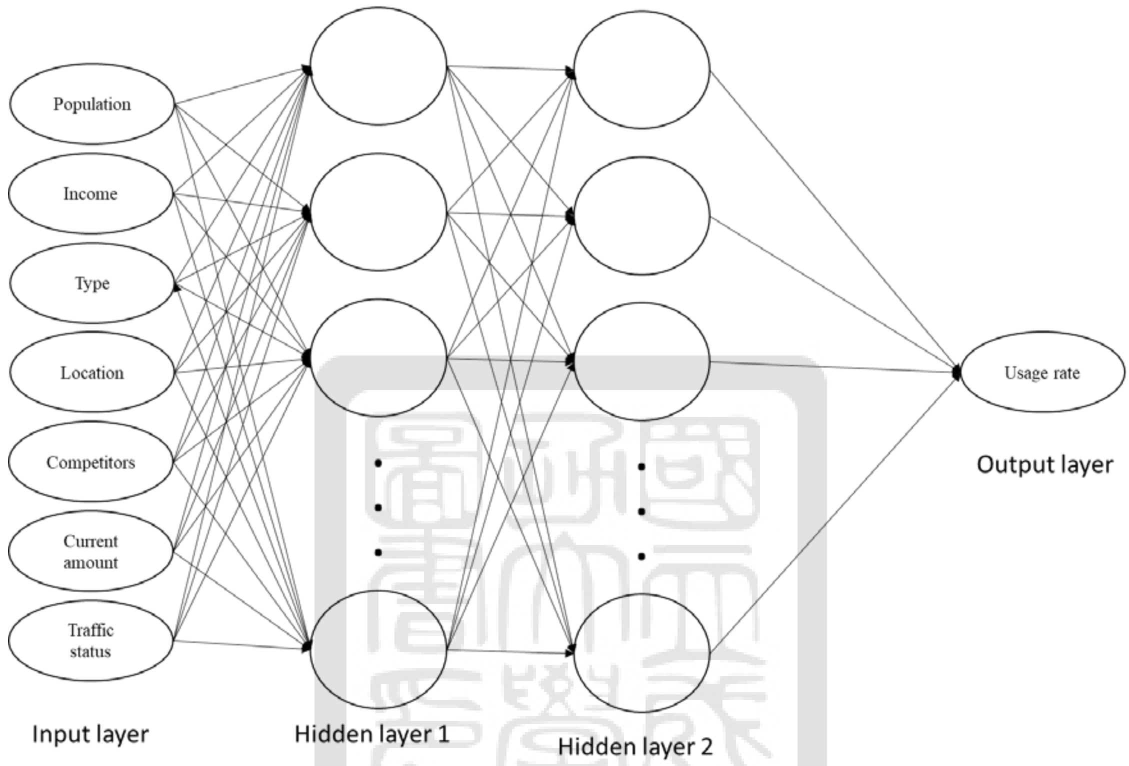

Figure 4.4 Proposed ANN model

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Table. 4.3 MAPE value of prediction models

Network name	MAPE	Network name	MAPE	Network name	MAPE	Network name	MAPE
11-20-20-1	9.98%	11-17-14-1	15.95%	11-17-19-1	16.70%	11-12-15-1	20.34%
11-16-19-1	9.99%	11-17-12-1	15.96%	11-20-15-1	17.06%	11-13-15-1	20.94%
11-20-13-1	10.08%	11-16-16-1	15.97%	11-15-17-1	17.16%	11-12-14-1	20.97%
11-16-13-1	10.12%	11-20-19-1	15.98%	11-19-13-1	17.56%	11-18-16-1	21.01%
11-20-18-1	10.25%	11-16-18-1	15.99%	11-19-20-1	17.63%	11-12-17-1	21.16%
11-17-13-1	10.57%	11-19-17-1	16.00%	11-17-18-1	17.70%	11-14-17-1	21.16%
11-19-14-1	10.76%	11-16-12-1	16.05%	11-19-15-1	17.75%	11-14-14-1	21.16%
11-19-16-1	11.01%	11-15-12-1	16.05%	11-19-12-1	18.01%	11-13-12-1	21.16%
11-17-16-1	11.12%	11-18-17-1	16.06%	11-18-12-1	18.69%	11-14-18-1	21.16%
11-18-20-1	11.68%	11-16-15-1	16.07%	11-19-19-1	18.70%	11-14-12-1	21.16%
11-20-14-1	11.68%	11-16-17-1	16.10%	11-15-14-1	18.83%	11-14-13-1	21.17%
11-18-18-1	12.01%	11-17-15-1	16.11%	11-20-17-1	18.87%	11-14-20-1	21.17%
11-15-18-1	12.02%	11-15-19-1	16.12%	11-12-13-1	18.92%	11-14-19-1	21.17%
11-13-16-1	12.05%	11-18-13-1	16.12%	11-15-20-1	18.97%	11-14-15-1	21.19%
11-17-20-1	12.11%	11-17-17-1	16.14%	11-13-19-1	19.08%	11-14-16-1	21.28%
11-19-18-1	13.79%	11-20-12-1	16.14%	11-18-15-1	19.19%	11-20-16-1	21.29%
11-13-20-1	14.96%	11-15-13-1	16.15%	11-12-20-1	19.57%	11-12-18-1	21.35%
11-12-12-1	15.20%	11-15-15-1	16.18%	11-16-14-1	19.69%	11-13-14-1	21.46%
11-18-14-1	15.59%	11-15-16-1	16.28%	11-13-18-1	19.86%	11-12-19-1	21.73%
11-18-19-1	15.89%	11-16-20-1	16.53%	11-12-16-1	20.16%	11-13-13-1	21.77%
						11-13-17-1	22.84%

The training parameters setting are described as follows:

1. Input layer- Hidden layer- Hidden layer- Output layer (units): 11-20-20-1
2. Training cycle: 3,000 times
3. Batch size: 10
4. Training data (%): 70%
5. Testing data (%): 30%
6. Validation data(%): 10% each in training and testing data
7. Activation function: Rectified Linear Unit(ReLU), Sigmoid

After the prediction model is constructed, the test data is entered and the output value is calculated. We can confirm the predictive ability of the model rely on performance indicators to assess. This study applied the accuracy and the mean absolute percentage error (MAPE) to evaluate the performance of the ANN model. The higher accuracy and smaller MAPE represent the learning ability and the effect of the model is better. Table 4.3 presents Lewis's benchmark (Lewis, 1982) that has been used to evaluate the performance of models forecasting. MAPE less than 10% pinpoints high accuracy; 10% to 20% means good

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performance; 20% to 50% is reasonable; more than 50% is inaccurate (Table 4.3). The following shows the calculation formula.

Table 4.4 Interpretation of typical MAPE values

MAPE	$\leq 10\%$	$10\% - 20\%$	$20\% - 50\%$	$\geq 50\%$
Evaluation	Highly accurate	Good	Reasonable	Inaccurate

Source: Lewis (1982)

$$\text{Accuracy} = \ 1 - \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Testing\ data_i - predicted_i}{Testing\ data_i}\right| \times 100\%\right)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Testing\ data_i - predicted_i}{Testing\ data_i}\right| \times 100\%$$

Table 4.4 shows the accuracy and MAPE of the model. The MAPE is less than 10%, it means the model perform highly accurate. Figure 4.6 illustrates the correlation between the testing data and the predictive output. The diagonal line represents the accurate prediction. The value above the diagonal line means overestimated; the value below the diagonal line is underestimated. Figure 4.7 shows the line graph of the relation with testing data and predictive output, we can find that the results presented by the graph are not far away from the results of the accuracy analysis. The trajectory of the trend between the testing data and the predicted results is approximately the same, which proves that the accuracy of the model prediction is quite accurate. We will also input the data of the candidate nodes into the ANN model to predict the usage rate of the facility.

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Table 4.5 Accuracy and MAPE results

Testing Performance		
Network structure	Accuracy	MAPE
11-20-20-1	90.02%	9.98%

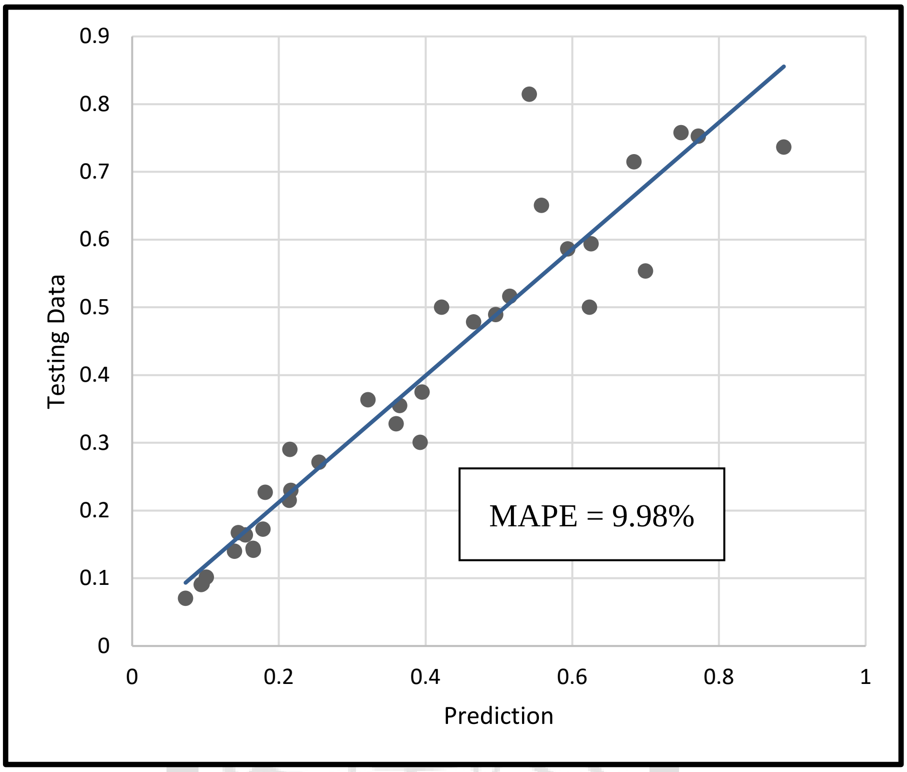

Figure 4.5 Correlation between testing data and prediction

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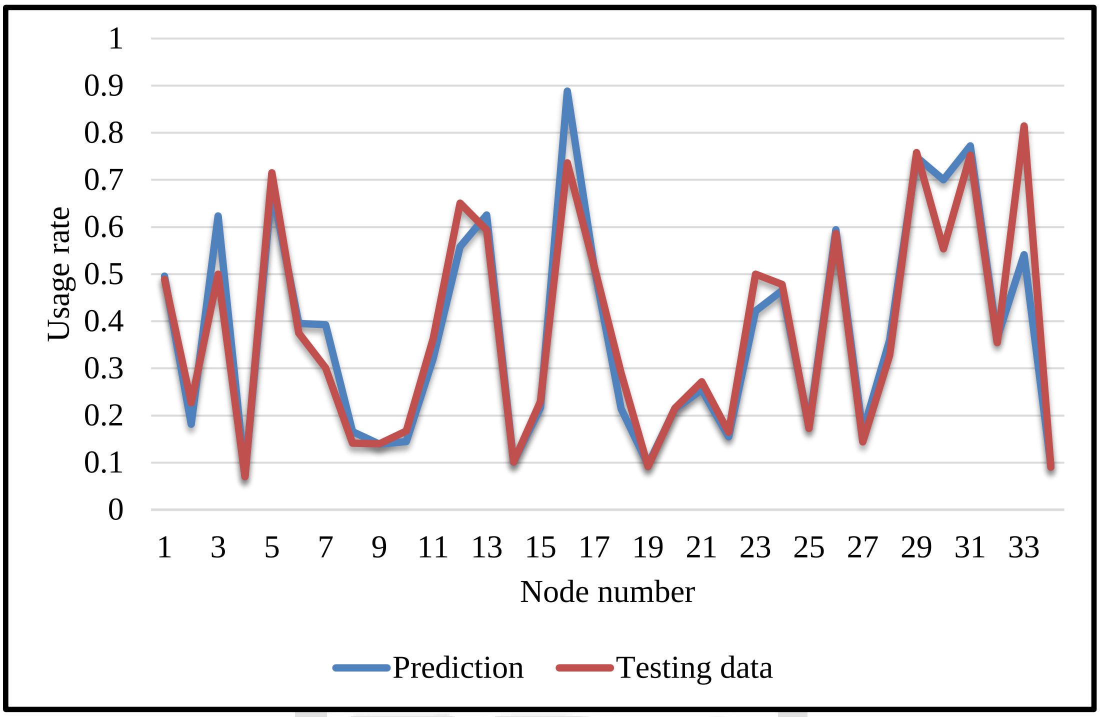

Figure 4.6 Line graph of predictive results

In this study, in order to discuss the influence of various variables on the prediction results in the ANN model, sensitivity analysis was used to rank the importance between variables. Sensitivity analysis has many different evaluation methods in different research categories, and this study uses Global Sensitivity Analysis (GSA). GSA is suitable for a nonlinear input-output relationship, and is more realistic to the real world since it allows all input factors to be varied simultaneously. GSA is the process of allocating the output uncertainty to the uncertainty of each input factor in the entire input range. When all input factors change simultaneously and the sensitivity is evaluated over the entire range of each input factor, the sensitivity analysis is considered to be global. It provides an overall view on the influence of inputs on outputs, rather than a partial local view of partial derivatives in the local sensitivity analysis (Saltelli et al., 2008).

Table 4.5 shows the ratio of GSA for each variable in the ANN model. This ratio is the network error of a given input divided by the network error of the original input. If the ratio

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is ≤ 1, the input variable does not affect predictive results. Additionally, sensitivity analysis can only assess the importance of input variables, so the study further applied Spearman correlation to learn the relevant direction based on rank correlation.

Through Table 4.5, we can understand the degree of relationship between each variable and predictive result. This study ranked the sensitivity ratio from high to low. Among all the variables, the sensitivity of each variable is greater than 1, which means that all variables will have different degrees of influence on the predictive result. Among them, street corners, traffic flow, distributor, alley, and roadside are more sensitive, and income, convenience store, gas station, comparator, current amount and population are variables with lower sensitivity. There are seven variables that not only own a higher sensitivity ratio, but also perform significantly related to the predictive result in spearman correlation. Among them, street corners (0.147 *), traffic status (0.614 **), distributors (0.238 **), competitors (0.164 *), current amount (0.163 *) and population (0.144 *) have a positive correlation to the predictive result; and convenience store (-0.186 **) has a negative correlation to the result, namely, the battery swapping station which is set up at street corner, has higher level of traffic status, is the type of distributor, has greater number of competitors, has greater number of nearby existing battery swapping station and has huge target population tends to have higher facilities usage rate, on the contrary, the station which is the type of convenience store tends to have lower facilities usage rate. Nevertheless, we are not trying to convey that the remaining variables that are not significantly related to Spearman correlation do not influence the predictive result. The remaining variables still have a certain degree of importance in the construction of the ANN model. For instance, although alley and roadside are not significantly correlated in Spearman correlation, they still have a relatively high degree of negative correlation in the ANN model.

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Table 4.6 Sensitivity and spearman correlation of each variable

Variable	Sensitivity ratio	Spearman correlation
Street corner (location)	1.967995	0.147*
Traffic status	1.722578	0.614**
Distributor (type)	1.694921	0.238**
Alley (location)	1.434236	-0.049
Roadside (location)	1.202849	-0.122
Income	1.109928	0.092
Convenience store (type)	1.100589	-0.186**
Gas station (type)	1.08039	0.0149
Competitor	1.002856	0.164*
Current amount	1.002731	0.163*
Population	1.001486	0.144*

4.4 Results analysis of optimization model

In this study, facilities' usage rate predicted by the ANN model is brought into the multi-objective optimization model to calculate the optimal setting location and the number of facilities with each site under the conditions of optimizing facility usage amount, demand coverage and total setting cost. This study designs four experimental scenarios under different cost constraints, namely NTD 30M, 40M, 50M and 60M, we try to discuss the results of optimization and what changes the results will produce. The overall results of the four scenarios are shown in Table 4.7 and Table 4.8. Table 4.7 shows the total number of

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setting nodes and classification of facilities amount in each node, and Table 4.8 shows the total number of setting nodes in each district of four different cost constraints.

Table 4.7 Classification of facilities amount and node

Budget constraint	Node (number)	Number of facilities							
		36	34	30	28	24	22	20	18
30M	32	8	0	8	0	0	0	0	16
40M	39	16	0	8	1	6	0	0	8
50M	50	18	5	6	0	4	0	0	17
60M	66	17	1	4	0	5	5	0	34

Table 4.8 Node distribution in four scenarios

Number	District	Total (nodes)	30M	40M	50M	60M
1	**Yongkang**	13	6	7	9	11
2	**South**	11	4	5	5	6
3	**West Central**	10	2	2	5	8
4	**East**	10	6	6	8	10
5	**Annan**	9	1	2	2	5
6	**North**	8	4	4	4	4
7	**Anping**	7	4	5	6	6
8	**Xinshi**	6	2	2	2	3
9	**Shanhua**	5	0	0	1	2
10	**Guiren**	4	1	2	3	3
11	**Guantian**	3	0	0	0	0
12	**Xinying**	2	2	2	2	2
13	**Xuejia**	2	0	1	1	1
14	**Jiangjun**	2	0	1	1	1
15	**Rende**	2	0	0	0	0
16	**Jiali**	2	0	0	1	1
17	**Yujing**	2	0	0	0	0
18	**Baihe**	1	0	0	0	1
19	**Madou**	1	0	0	0	0
20	**Shanshang**	1	0	0	0	0
21	**Xigang**	1	0	0	0	0

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22	**Houbi**	1	0	0	0	0
23	**Danei**	1	0	0	0	0
24	**Beimen**	1	0	0	0	0
25	**Zuozhen**	1	0	0	0	0
26	**Liuying**	1	0	0	0	0
27	**Longqi**	1	0	0	0	0
28	**Guanmiao**	1	0	0	0	1
29	**Yanshui**	1	0	0	0	1
30	**Anding**	1	0	0	0	0
	Total	111	32	39	50	66

Table 4.9 to 4.12 reveals each setting type, the total number of nodes and facilities in each district of four different cost constraints, and Figure 4.7 to 4.10 show distribution graph of nodes' type and number. In 30M, there are setting 32 nodes in 10 districts, among all the setting nodes, 8 nodes are distributors, 11 nodes are gas station and 13 nodes are convenience store; there are 816 facilities in all setting nodes. In 40M, there are setting 39 nodes in 12 districts, among all the setting nodes, 11 nodes are distributors, 12 nodes are gas station and 16 nodes are convenience store; there are 1132 facilities in all setting nodes. In 50M, there are setting 50 nodes in 14 districts, among all the setting nodes, 15 nodes are distributors, 13 nodes are gas station and 22 nodes are convenience store; there are 1400 facilities in all setting nodes. In 60M, there are setting 66 nodes in 17 districts, among all the setting nodes, 15 nodes are distributors, 17 nodes are gas station and 34 nodes are convenience store; there are 1608 facilities in all setting nodes.

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Table 4.9 Optimal results with 30M budget

Budget	Number (district)	Type (number of facility)	D	G	C	Node	Facility
30M	1	D(18) G(18) C(18) C(18) C(18) C(18)	1	1	4	6	108
	2	D(30) G(18) C(18) C(18)	1	1	2	4	84
	3	G(30) G(18)	0	2	0	2	48
	4	D(36) D(36) G(36) G(36) G(36) G(18)	2	4	0	6	198
	5	G(18)	0	1	0	1	18
	6	D(36) D(36) D(30) G(30)	3	1	0	4	132
	7	C(30) C(30) C(30) C(18)	0	0	4	4	108
	8	C(18) C(18)	0	0	2	2	36
	10	C(18)	0	0	1	1	18
	12	G(36) D(30)	1	1	0	2	66
		total	8	11	13	32	816

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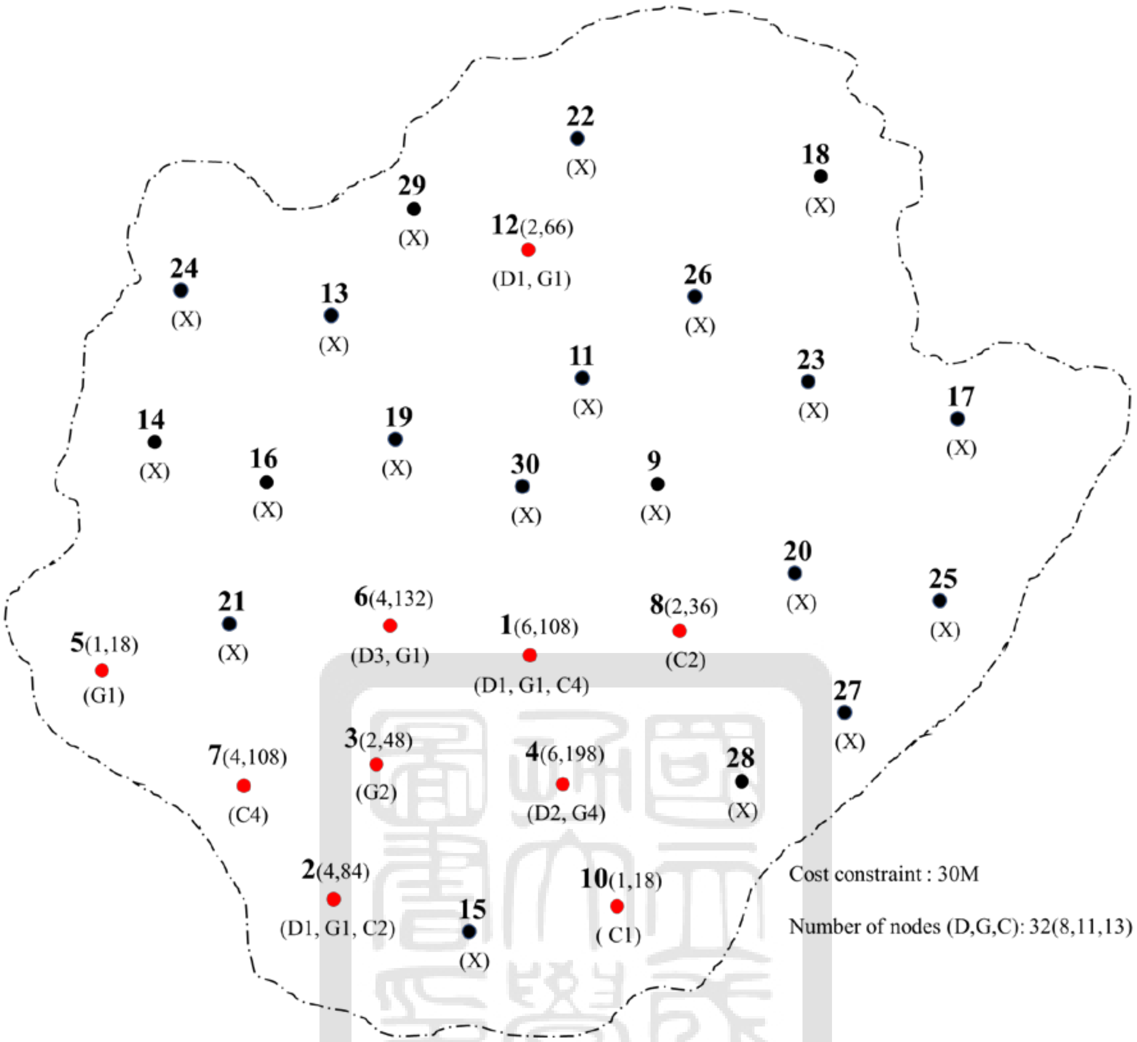

● Unselected node

● Selected node

G1 : Number(1) of nodes set in gas station

C1 : Number(1) of nodes set in convenience store

D1 : Number(1) of nodes set in distributor

1(2,60) : District number(total number of nodes, facilities amount)

Figure 4.7 Distribution graph of optimal result (30M)

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Table 4.10 Optimal results with 40M budget

Budget	Number (district)	Type (number of facility)	D	G	C	Node	Facility
40M	1	C(30) G(30) D(24) C(24) C(24) C(24) D(18)	2	1	4	7	174
	2	D(36) G(30) C(28) C(24) C(18)	1	1	3	5	136
	3	G(36) G(24)	0	2	0	2	60
	4	D(36) D(36) G(36) G(36) G(36) G(30)	2	4	0	6	210
	5	G(30) D(18)	1	1	0	2	48
	6	D(36) D(36) D(36) G(36)	3	1	0	4	144
	7	C(36) C(36) C(36) C(30) C(18)	0	0	5	5	156
	8	C(30) C(18)	0	0	2	2	48
	10	C(30) D(18)	1	0	1	2	48
	12	D(36) G(36)	1	1	0	2	72
	13	C(18)	0	0	1	1	18
	14	G(18)	0	1	0	1	18
		total	11	12	16	39	1132

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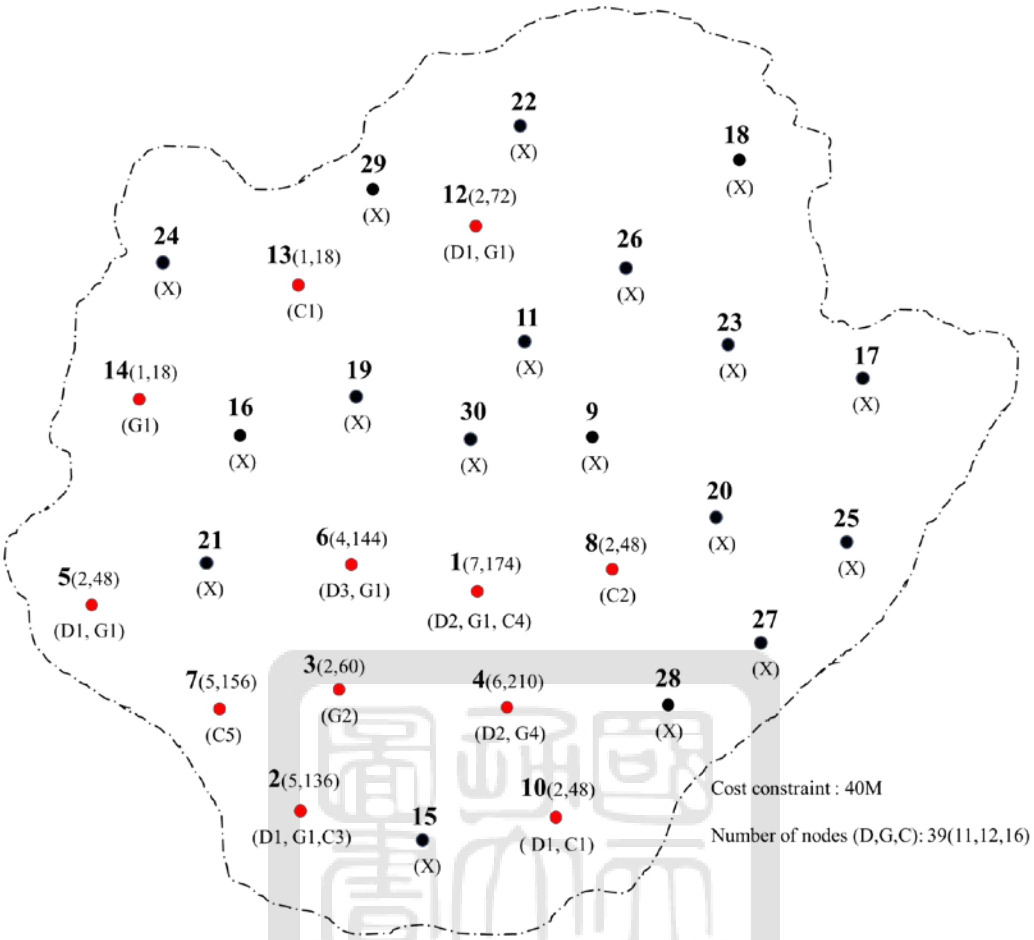

Figure 4.8 Distribution graph of Optimal results (40M)

Table 4.11 Optimal results with 50M budget

Budget	Number (district)	Type (number of facility)	D	G	C	Node	Facility
50M	1	G(34) C(34) C(30) D(30) C(24) C(24) C(18) C(18) D(18)	2	1	6	9	230
	2	D(36) G(36) C(30) C(30) C(24)	1	1	3	5	156
	3	G(36) G(30) D(18) C(18) C(18)	1	2	2	5	120
	4	D(36) D(36) G(36) G(36) G(36) G(34) D(18) C(18)	3	4	1	8	250
	5	G(30) D(18)	1	1	0	2	48
	6	D(36) D(36) D(36) G(36)	3	1	0	4	144

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	7	C(36) C(36) C(36) C(36) D(18) C(18)	1	0	5	6	180
	8	C(34) C(24)	0	0	2	2	58
	9	C(18)	0	0	1	1	18
	10	C(34) D(18) G(18)	1	1	1	3	70
	12	D(36) G(36)	1	1	0	2	72
	13	C(18)	0	0	1	1	18
	14	G(18)	0	1	0	1	18
	16	D(18)	1	0	0	1	18
		total	15	13	22	50	1400

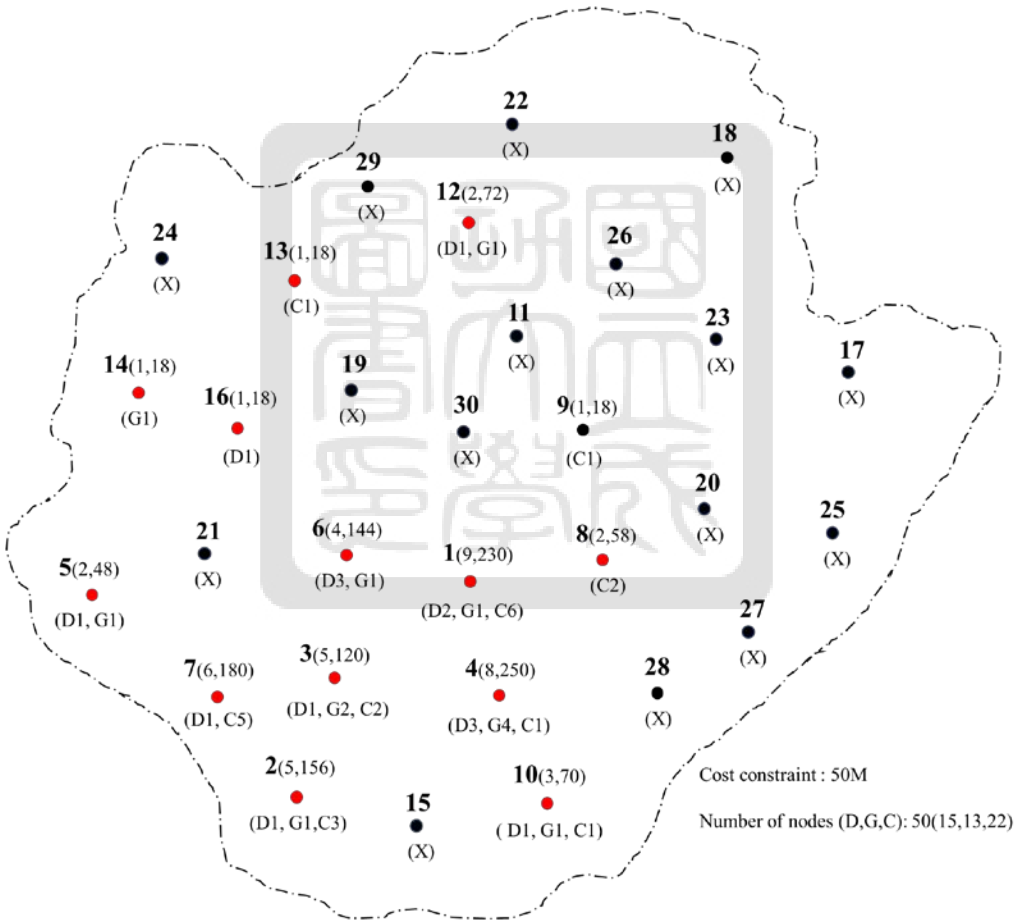

Figure 4.9 Distribution graph of optimal results (50M)

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Table 4.12 Optimal results with 60M budget

<table>
<tr><th>Budget</th><th>Number
(district)</th><th>Type
(number of facility)</th><th>D</th><th>G</th><th>C</th><th>Node</th><th>Facility</th></tr>
<tr><td rowspan="19">60M</td><td>1</td><td>C(30) G(24) C(24) C(22) C(22) D(22) C(18) C(18) C(18) C(18) D(18)</td><td>2</td><td>1</td><td>8</td><td>11</td><td>234</td></tr>
<tr><td>2</td><td>D(36) G(34) C(24) C(24) G(18) C(18)</td><td>1</td><td>2</td><td>3</td><td>6</td><td>154</td></tr>
<tr><td>3</td><td>G(36) G(22) D(18) G(18) C(18) C(18) C(18) C(18)</td><td>1</td><td>3</td><td>4</td><td>8</td><td>166</td></tr>
<tr><td>4</td><td>D(36) D(36) G(36) G(36) G(36) G(30) D(18) C(18) C(18) C(18)</td><td>3</td><td>4</td><td>3</td><td>10</td><td>282</td></tr>
<tr><td>5</td><td>G(24) D(18) C(18) C(18) C(18)</td><td>1</td><td>1</td><td>3</td><td>5</td><td>96</td></tr>
<tr><td>6</td><td>D(36) D(36) D(36) G(36)</td><td>3</td><td>1</td><td>0</td><td>4</td><td>144</td></tr>
<tr><td>7</td><td>C(36) C(36) C(36) C(36) D(18) C(18)</td><td>1</td><td>0</td><td>5</td><td>6</td><td>180</td></tr>
<tr><td>8</td><td>C(30) C(22) G(18)</td><td>0</td><td>1</td><td>2</td><td>3</td><td>70</td></tr>
<tr><td>9</td><td>C(18) C(18)</td><td>0</td><td>0</td><td>2</td><td>2</td><td>36</td></tr>
<tr><td>10</td><td>C(30) D(18) G(18)</td><td>1</td><td>1</td><td>1</td><td>3</td><td>66</td></tr>
<tr><td>12</td><td>D(36) G(36)</td><td>1</td><td>1</td><td>0</td><td>2</td><td>72</td></tr>
<tr><td>13</td><td>G(18)</td><td>0</td><td>1</td><td>0</td><td>1</td><td>18</td></tr>
<tr><td>14</td><td>G(18)</td><td>0</td><td>1</td><td>0</td><td>1</td><td>18</td></tr>
<tr><td>16</td><td>D(18)</td><td>1</td><td>0</td><td>0</td><td>1</td><td>18</td></tr>
<tr><td>18</td><td>C(18)</td><td>0</td><td>0</td><td>1</td><td>1</td><td>18</td></tr>
<tr><td>28</td><td>C(18)</td><td>0</td><td>0</td><td>1</td><td>1</td><td>18</td></tr>
<tr><td>29</td><td>C(18)</td><td>0</td><td>0</td><td>1</td><td>1</td><td>18</td></tr>
<tr><td></td><td>total</td><td>15</td><td>17</td><td>34</td><td>66</td><td>1608</td></tr>
</table>

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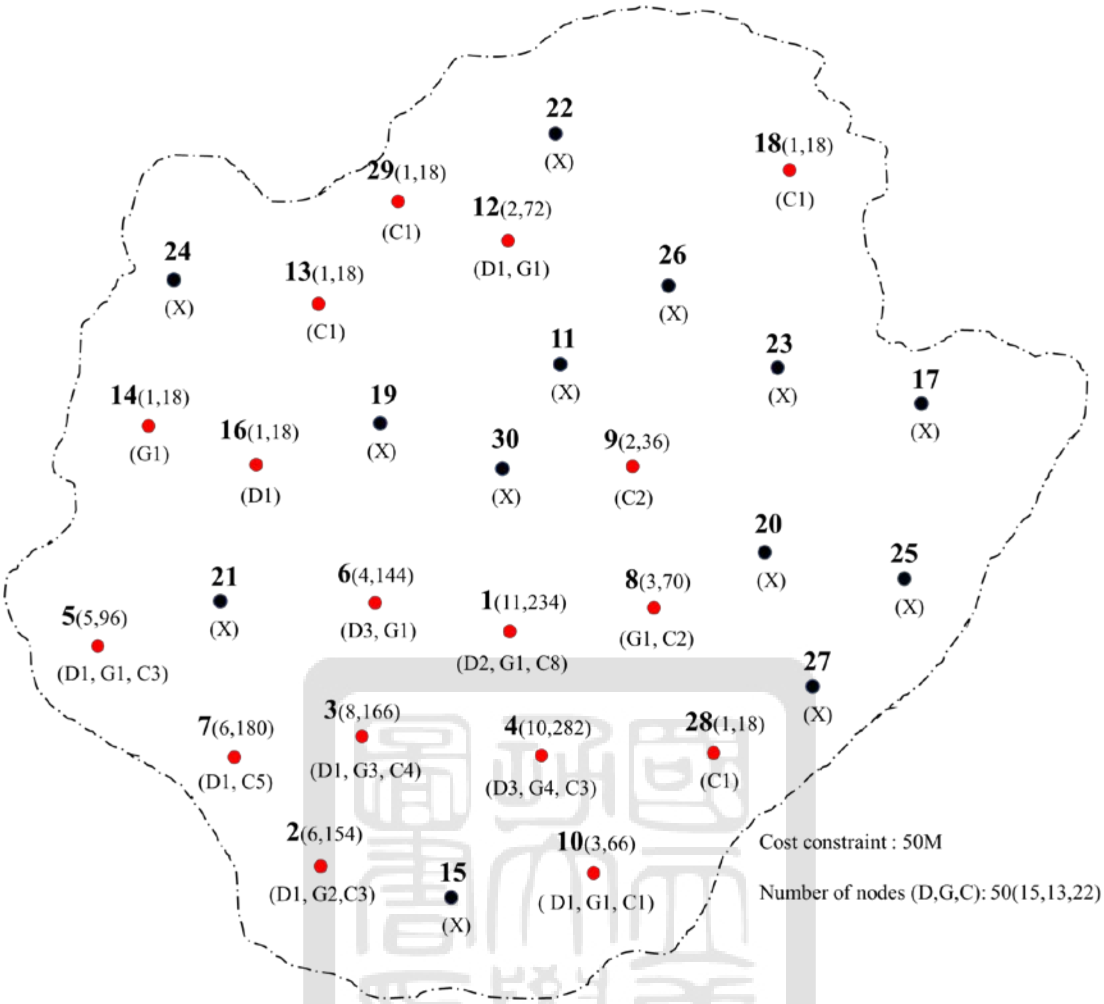

Figure 4.10 Distribution graph of optimal results (60M)

In this study, the multi-objective results are presented as a line graph. In four experimental scenarios, all budgets were exhausted, and the demand coverage and usage amount of facility were maximized under each cost constraint. The results are shown in the figures. Figure 4.12 shows the number of maximum covered population in each cost constraint. We can find that the rate of change between 50M and 60M is the largest, which represents 60M is the fastest growing stage of the covered population. However, In Figure 4.13, we find that between 50M and 60M is the stage with the largest decrease in usage amount, thus, the most likely reason we believe is that when the budget is increased to a certain level, the number of its optimal location and covered population will also increase.

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Similarly, the more rural locations will also be included in node selection, and too many rural stations will cause a decline in facility utilization.

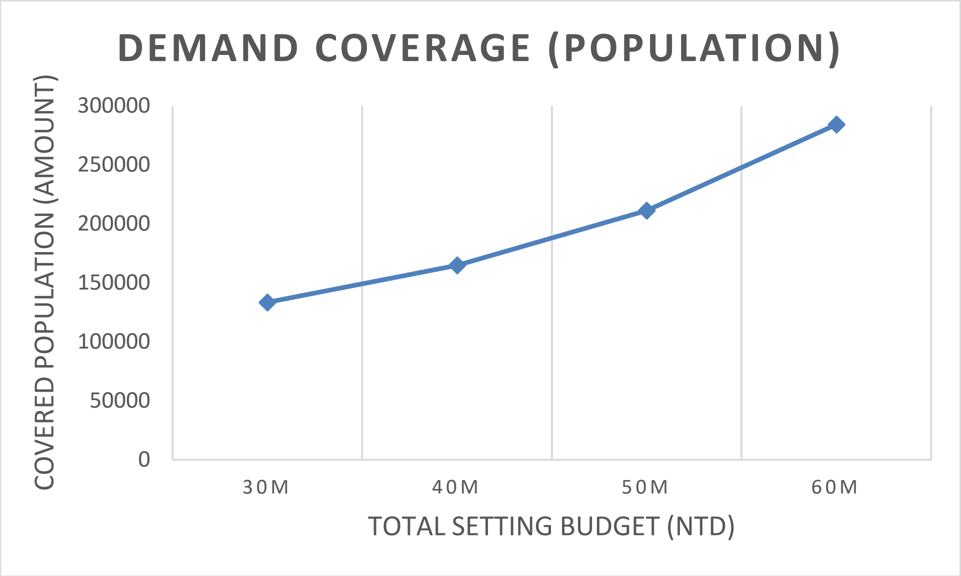

Figure 4.11 Line graph of covered population

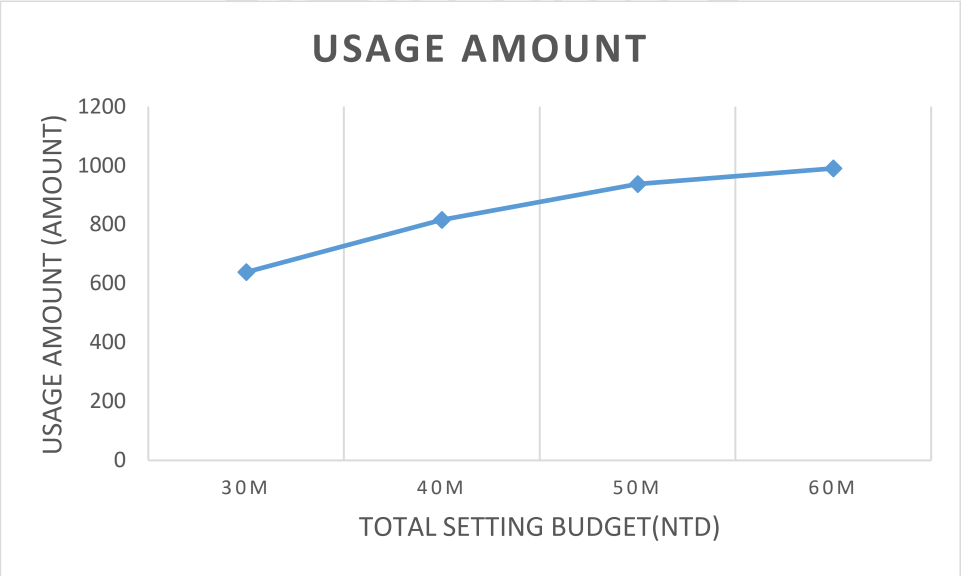

Figure 4.12 Line graph of usage amount

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4.5 Model extension

In this section, we propose two extended models that are adjusted according to the real-world condition, such as a hybrid optimization model with location set covering problem and optimization model with different weight considerations.

4.5.1 Hybrid optimization model with location set covering problem

The original objective of this study was to maximize the facility usage amount and demand coverage. However, actual policy and development are often not so simple. Adherence to a particular pattern is not sufficient to cover the requirements of diversity. If commercial operators or government want to take into account the concepts of social equity, balanced regional development and corporate social responsibility, they will seriously consider that each district must add at least one battery swapping station within the limited budget constraint.

In order to cover facilities in each district, we incorporated mathematical formula of location set covering problem into the original model and became a new hybrid model. The hybrid model can simultaneously solve the results of maximum facility usage amount and demand coverage under the condition that each district has at least one battery swapping station. The addition formulation of the hybrid model is as follows:

Notation:

$x_d =$ 1 if a facility is allocated in district d, 0 if not

$c_j =$ fixed cost of siting a facility at node j

N_j = set of facility node j within acceptable distance of district d

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Formulation:

$$Min\ Td_j = \sum_{j\in N}\sum_{d\in N} c_j X_d \qquad (4.1)$$

$$s.t. \sum_{d\in N} X_d \geq 1 \qquad ,\forall j \qquad (4.2)$$

$$X_d \in \{0,1\} \qquad ,\forall d \qquad (4.3)$$

The objective function (4.1) minimizes the cost of facility location. Constraint (4.2) requires that all districts d have at least one facility located. Constraint (4.3) requires integrality for the decision variables. In addition, the complete mathematical programming model is as follows:

$$Max\ TU_j = \sum_{j\epsilon N} X_j P_j \qquad (3.1)$$

$$Max\ Th_j = \sum_{i\in N}\sum_{j\epsilon N} g_i Y_j \qquad (3.2)$$

$$Min\ Td_j = \sum_{j\in N}\sum_{d\in N} c_j X_d \qquad (4.1)$$

Objective function

$$Max\ Z = W_1 TU_j + W_2 Th_j + W_3 Td_j \qquad (3.3)$$

Subject to

$$\sum_{j\epsilon N} Y_j \leq \beta \qquad (3.4)$$

$$\sum_{j\epsilon N} (C_v X_j + C_f) Y_j \leq \bar{C} \qquad (3.5)$$

$$X_j \leq MY_j \qquad ,\forall \in \ S' \qquad (3.6)$$

$$Y_j \leq 1 \qquad ,\forall j \in S' \qquad (3.7)$$

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$$F^{min} \leq X_j \leq F^{max} \qquad ,\forall j \in S' \tag{3.8}$$

$$\sum_{d \in N} X_d \geq 1 \qquad ,\forall j \tag{4.2}$$

$$Y_j \in \{0,1\} \qquad ,i\forall \in S, \forall j \in S' \tag{3.9}$$

$$X_d \in \{0,1\} \qquad ,\forall d \tag{4.3}$$

$$C_v, C_f, F^{min}, F^{min}, P_j, X_j \geq 0 \qquad ,\forall j \in S' \tag{3.10}$$

We set two different budget constraints, 30M and 60M respectively. The results are as follows , Table 4.13 shows the total number of setting nodes in each district of two different budget constraints. Table 4.14 and 4.15 reveals each setting type, the total number of nodes and facilities in each district of two different budget constraints, In 30M, there are setting 36 nodes in 30 districts, among all the setting nodes, 7 nodes are distributors, 12 nodes are gas station and 17 nodes are convenience store; there are 768 facilities in all setting nodes. In 60M, there are setting 69 nodes in 30 districts, among all the setting nodes, 15 nodes are distributors, 21 nodes are gas station and 33 nodes are convenience store; there are 1572 facilities in all setting nodes. Some districts have a great difference in node number between 30M and 60M budget constraints, such as Yongkang, West Central and Anping. On the contrary, the other districts have little difference in node number. The reason probability is that districts with high population density and predicted usage amount generally have more candidate nodes, and when the budget increases, these districts have a higher probability of being selected.

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Table 4.13 Node distribution in hybrid model

Number	District	Total (nodes)	30M	60M
1	**Yongkang**	13	1	9
2	**South**	11	1	5
3	**West Central**	10	1	7
4	**East**	10	5	8
5	**Annan**	9	1	2
6	**North**	8	2	4
7	**Anping**	7	1	6
8	**Xinshi**	6	1	3
9	**Shanhua**	5	1	1
10	**Guiren**	4	1	3
11	**Guantian**	3	1	1
12	**Xinying**	2	2	2
13	**Xuejia**	2	1	1
14	**Jiangjun**	2	1	1
15	**Rende**	2	1	1
16	**Jiali**	2	1	1
17	**Yujing**	2	1	1
18	**Baihe**	1	1	1
19	**Madou**	1	1	1
20	**Shanshang**	1	1	1
21	**Xigang**	1	1	1
22	**Houbi**	1	1	1
23	**Danei**	1	1	1
24	**Beimen**	1	1	1
25	**Zuozhen**	1	1	1
26	**Liuying**	1	1	1
27	**Longqi**	1	1	1
28	**Guanmiao**	1	1	1
29	**Yanshui**	1	1	1
30	**Anding**	1	1	1
	Total	111	36	69

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Table 4.14 Optimal results with 30M budget (hybrid model)

Budget	Number (district)	Type (number of facility)	D	G	C	Node	Facility
	1	C(18)	0	0	1	1	18
	2	D(20)	1	0	0	1	20
	3	G(20)	0	1	0	1	20
	4	D(36) D(36) G(36) G(36) G(36)	2	3	0	5	180
	5	G(18)	0	1	0	1	18
	6	D(20) D(20)	2	0	0	2	40
	7	C(20)	0	0	1	1	20
	8	C(18)	0	0	1	1	18
	9	C(18)	0	0	1	1	18
	10	C(18)	0	0	1	1	18
	11	G(18)	0	1	0	1	18
	12	G(36) D(20)	1	1	0	2	56
	13	C(18)	0	0	1	1	18
	14	G(18)	0	1	0	1	18
	15	G(18)	0	1	0	1	18
30M	16	D(18)	1	0	0	1	18
	17	C(18)	0	0	1	1	18
	18	C(18)	0	0	1	1	18
	19	C(18)	0	0	1	1	18
	20	G(18)	0	1	0	1	18
	21	G(18)	0	1	0	1	18
	22	G(18)	0	1	0	1	18
	23	C(18)	0	0	1	1	18
	24	C(18)	0	0	1	1	18
	25	G(18)	0	0	1	1	18
	26	C(18)	0	0	1	1	18
	27	C(18)	0	0	1	1	18
	28	C(18)	0	0	1	1	18
	29	C(18)	0	0	1	1	18
	30	C(18)	0	0	1	1	18
		total	7	12	17	36	768

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Table 4.15 Optimal results with 60M budget (hybrid model)

Budget	Number (district)	Type (number of facility)	D	G	C	Node	Facility
60M	1	G(24) C(24) C(24) D(18) D(18) C(18) C(18) C(18) C(18)	2	1	6	9	180
	2	D(30) G(24) C(24) C(24) C(18)	1	1	3	5	120
	3	G(36) G(24) D(18) G(18) C(18) C(18) C(18)	1	3	3	7	150
	4	D(36) D(36) G(36) G(36) G(36) G(24) D(18) C(18)	3	4	1	8	240
	5	G(24) D(18)	1	1	0	2	42
	6	D(36) D(36) D(30) G(30)	3	1	0	4	132
	7	C(30) C(30) C(30) C(30) D(18) C(18)	1	0	5	6	156
	8	C(24) G(18) C(18)	0	1	2	3	60
	9	C(18)	0	0	1	1	18
	10	C(24) D(18) G(18)	1	1	1	3	60
	11	G(18)	0	1	0	1	18
	12	D(36) G(36)	1	1	0	2	72
	13	C(18)	0	0	1	1	18
	14	G(18)	0	1	0	1	18
	15	G(18)	0	1	0	1	18
	16	D(18)	1	0	0	1	18
	17	C(18)	0	0	1	1	18
	18	C(18)	0	0	1	1	18
	19	C(18)	0	0	1	1	18
	20	G(18)	0	1	0	1	18
	21	G(18)	0	1	0	1	18
	22	G(18)	0	1	0	1	18
	23	C(18)	0	0	1	1	18
	24	C(18)	0	0	1	1	18
	25	G(18)	0	1	0	1	18
	26	C(18)	0	0	1	1	18
	27	C(18)	0	0	1	1	18
	28	C(18)	0	0	1	1	18
	29	C(18)	0	0	1	1	18

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	30	C(18)	0	0	1	1	18
		total	15	21	33	69	1572

4.5.2 Various weight considerations of optimization model

The above results are considered the same weight of the multi-objective model, however, in the real world, different decision-makers will give distinct weights according to various objectives. Therefore, this study respectively to calculate the other two schemes to give decision-makers more multivariate reference, respectively facilities usage rate: demand coverage (2:1), facility usage rate: demand coverage (1:2). The analysis indicated that scheme (1:1) performed moderately in the whole site location optimization, it was even the worst in terms of facility usage amount, however, the demand coverage of the scheme is the fastest-growing between 50M and 60M. Scheme (2:1) performed better in facility usage amount and the number of facilities, but performed worst in demand coverage and the number of nodes. Scheme (1:2) performed better in demand coverage and number of nodes, but performed worst in the number of batteries. The results seem reasonable that if decision-makers were more concerned about facility usage amount they would try to fit more facilities into locations that perform well in usage prediction and avoid setting up sites in locations that do poorly on usage prediction. Conversely, decision-makers who care more about demand coverage will tend to cover the largest population with limited resources. Decision-makers who are more concerned about the facility usage amount will set more batteries within a small number of node, whereas decision-makers who are concerned about demand coverage will set wider nodes as their main goal.

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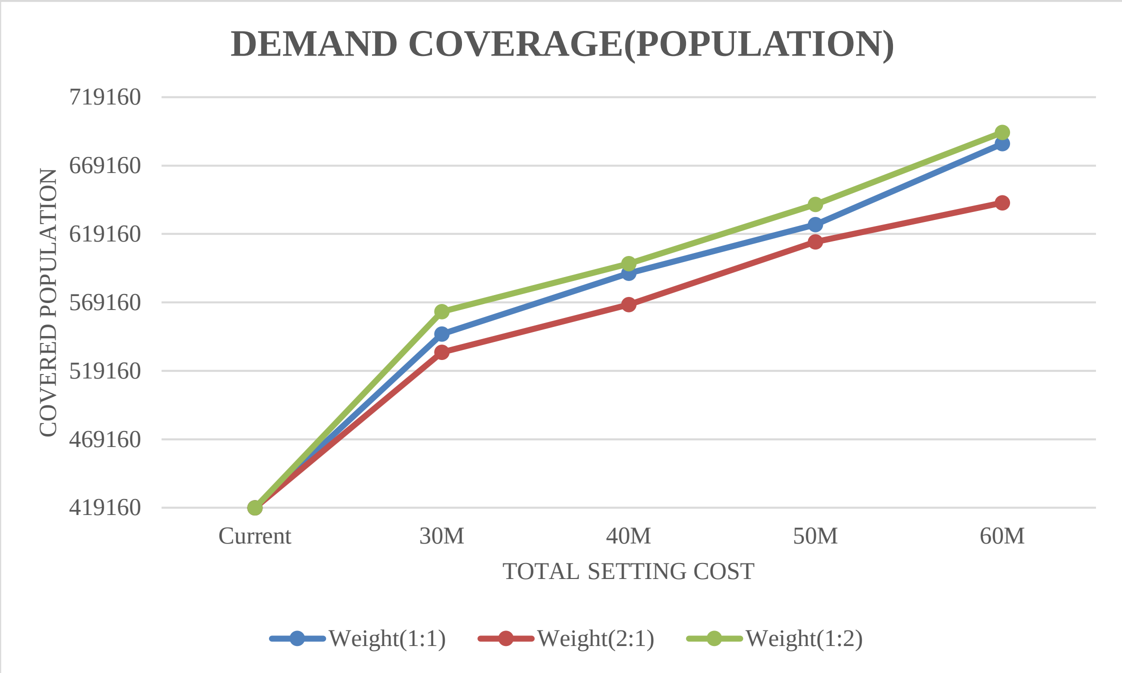

Figure 4.13 Line graph of covered population in three schemes

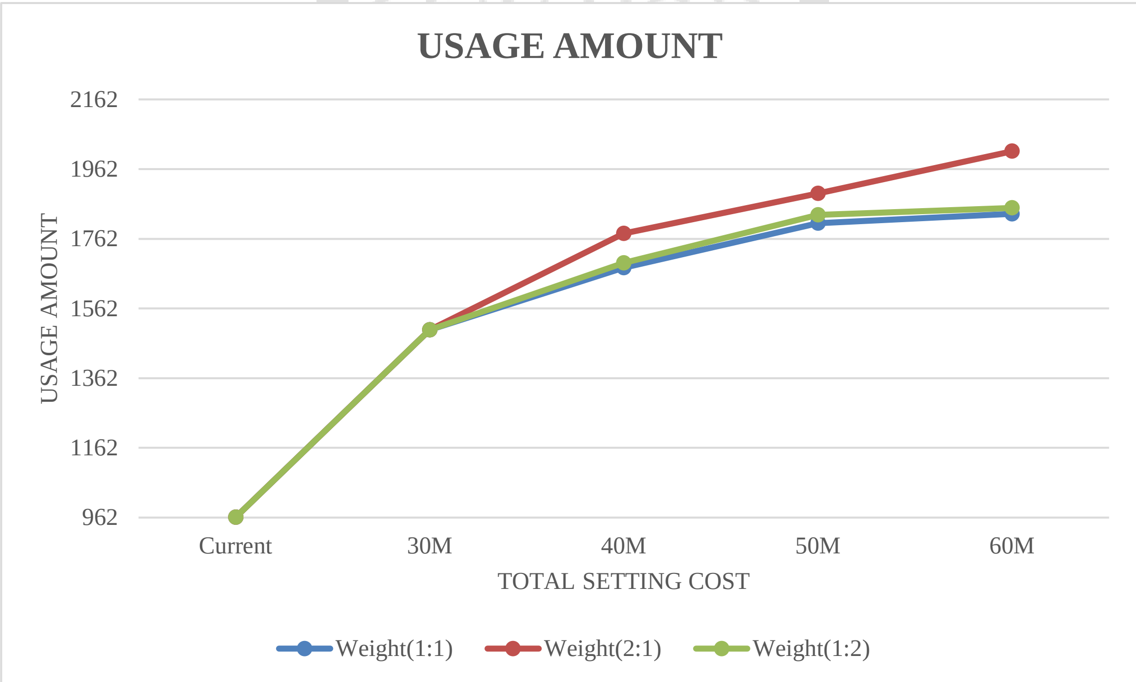

Figure 4.14 Line graph of usage amount in three schemes

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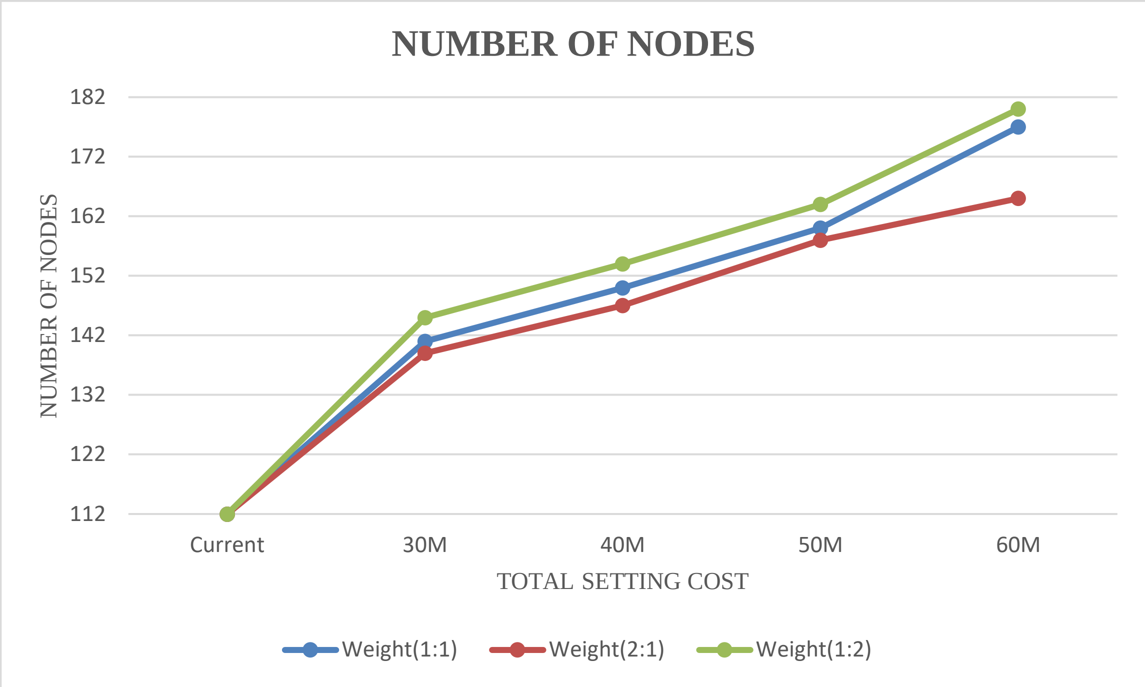

Figure 4.15 Line graph of nodes number in three schemes

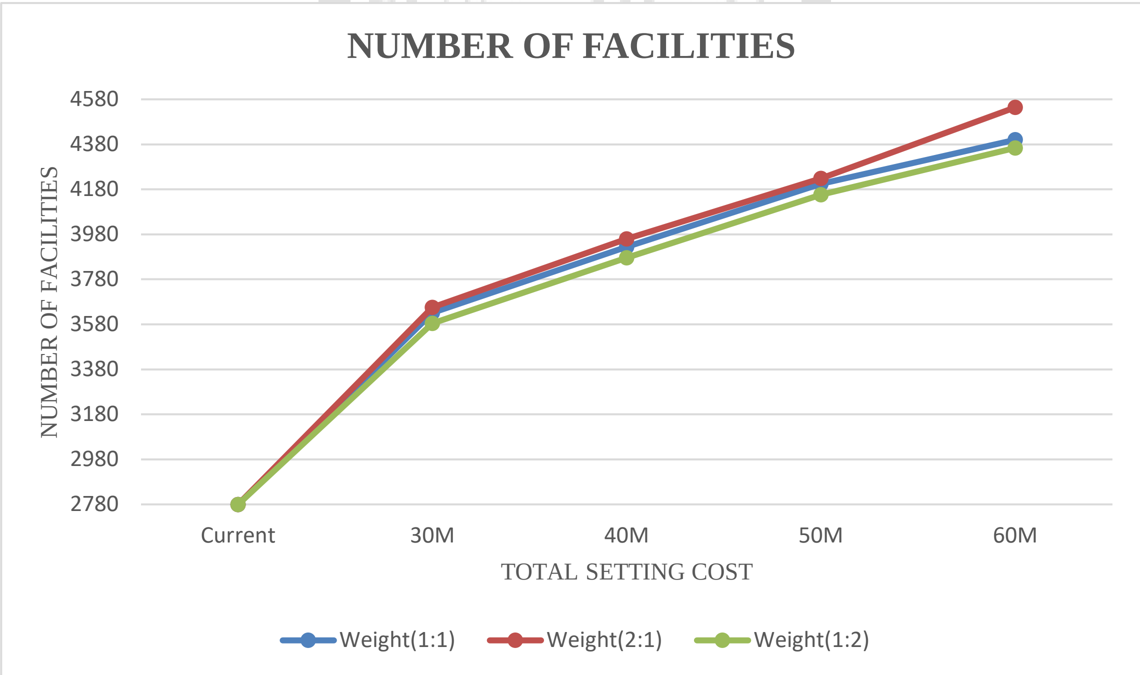

Figure 4.16 Line graph of facilities number in three schemes

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CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

This study proposes the ANN model and multi-objective optimization model to solving battery swapping stations location problems for ESs. From the empirical study results, we summarize the conclusions and recommendations in Section 5.1 and Section 5.2.

5.1 Conclusions

The proposed models aim to determine the optimal locations and number of facilities for four different cost constraints, from the results of the empirical studies, the conclusions of this study are summarized as follows:

1. The proposed ANN model has a 90% accuracy in predicting the usage rate of facilities, which represents that ANN is suitable for predicting usage rate of battery swapping station for ESs.
2. The results of the empirical study show the capability of the proposed models for the ESs battery swapping station location problem, it can accurately estimate the most appropriate setting location and the number of facilities under different budget constraints.
3. 112 realistic stations and 111 candidate locations are selected as the demonstrative nodes in the empirical study. Four experiment scenarios were designed to explore the locations and number of facilities.
4. We found that the rates of change of the covered population and usage amount in the first three scenarios all increased steadily and linearly, but the different changes occurred in the fourth scenario. The problem is too many rural stations have been selected, therefore, we suggest that the government or commercial operators can make

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a trade-off between demand coverage and facility utilization to achieve the most suitable and optimal development direction.

5. From the sensitivity analysis, it can be found that street corner, traffic status, distributors, alley and roadside are the top five variables that affect the usage rate of facilities, among them, street corner, traffic status and distributor are positive correlation; alley and roadside are negative correlation to facility usage rate.
6. In this study, three schemes with different weight allocation are considered respectively, and the analysis results are in accordance with the considerations of decision-makers in the real world. The decision-makers who concerned more about facility usage amount they would try to fit more facilities into locations that perform well in usage prediction, and who care more about demand coverage will tend to cover the largest population with limited resources.

5.2 Recommendations

1. In this study, almost all the data is realistic but the only station and facility setting cost are assumed, thus, it is recommended that future research can complete the model with realistic cost data.
2. The research scope in this study is Tainan city, this study suggests that future research can obtain more sample data from other regions for prediction and optimization research, and compare whether different regions will produce different research results.
3. This study does not consider the overlapping of demand coverage of multiple neighboring nodes. Future research can address this problem to explore the different effects of overlapping coverage areas.

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4. In this study, only the ANN model was used to predict the usage rate of facilities, therefore, it was suggested that more prediction methods could be used in future studies to compare the pros and cons of various methods.

5. Although there is a correlation between the usage rate of facilities and the demand for battery swapping stations, there is still a gap in essence. It is suggested that future studies can assess the overall demand from the perspective of consumers.

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