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RESEARCH ARTICLE

Optimization and Observation of EV Charging Station Deployment in the Republic of Korea: An Analysis of the Charging History and Correlation With Socioeconomic Factors

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ABSTRACT The demand for electric vehicles is increasing due to the recent focus on reducing greenhouse gas emissions. Hence, the number of electric-vehicle charging stations must be increased to meet the growing demand for electric vehicles. To this end, supportive policies are being established to increase the deployment of electric vehicle charging stations worldwide. On the other hand, it is not possible to subsidize all facilities simultaneously. This study developed a model to prioritize the deployment of electric vehicle charging stations. The Republic of Korea was analyzed as a case study region to develop this model, and the correlations between the amount of charging energy of electric vehicle charging stations and socioeconomic factors (traffic volume, population, number of electric vehicles, and land value) were analyzed. The correlations were analyzed differently depending on the purpose (e.g., residential or commercial) of the facilities where electric vehicle charging stations were installed. Correlation analysis was conducted to determine the factors that affect the amount of charging energy, and a model was developed to prioritize the deployment of electric vehicle charging stations through a genetic algorithm. A model with a correlation of more than 0.2 was developed, except for residential facilities with slow chargers and public institutions with slow chargers. The results of this paper can help identify the key factors to be analyzed by facility use when installing electric vehicle charging stations and determine the priorities for subsidizing the deployment of electric vehicle charging stations.

INDEX TERMS Charging stations, correlation coefficient, electric vehicle, genetic algorithm, slow and fast chargers.

ABBREVIATIONS

GHG	Greenhouse gas.
EV	Electric vehicle.
KOSIS	Korean statistical information service.
AADT	Annual average daily traffic.
KTDB	Korea transportation data base.
MOLIT	Ministry of land, infrastructure and transport.
CPO	Charging points operator.

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I. INTRODUCTION

A. BACKGROUND

People are becoming increasingly concerned about climate change. As a result, international attention and efforts to reduce greenhouse gas (GHG) are also increasing. According to the source of GHGs, 23% of the total GHGs are

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generated by transportation, and 74% of the GHGs generated by transportation are generated by vehicles on the road [1]. Therefore, increasing the number of electric vehicles (EVs) will help reduce GHG emissions. In recent years, the public interest in EVs has increased as public awareness of climate change has increased [2], which can reduce GHG emissions and air pollutants [3], [4]. As a result, sales of EVs have been increasing steadily [5]. This increase in EV penetration will help reduce GHG emissions on the road. Therefore, the number of EV charging stations to cope with this increase in the number of EVs and the increased penetration rate. Many studies have reported that EV charging stations are essential for increasing EV penetration [6], [7], [8]. A survey in the Republic of Korea showed that the lack of EV charging stations is one of the main reasons for hesitation in purchasing an EV [9].

Governments are mandating the deployment of EV charging stations to address the lack of EV charging stations. There are many different policies, but several countries have mandated the installation of EV charging stations by a specific year and provide subsidies for doing so [10], [11], [12], [13]. Nevertheless, it would be impossible to provide all the subsidies to all the buildings that are required to install EV charging stations (this depends on each country's regulations) at the same time, so some countries (e.g., Republic of Korea and Germany) have decided to provide subsidies on a first-come, first-served basis [10], [13]. This might not consider the facilities that should be prioritized for EV charging (i.e., those with high demand for EV charging). Hence, EV charging stations may be deployed in facilities that do not currently have a high demand for EV charging, resulting in underutilized EV charging stations. This is an unnecessary waste of budget that leads to insufficient EV charging stations being deployed in regions with high demand for EV charging and unnecessary deployment in regions with low demand for EV charging, leaving EV charging stations unused. Indeed, the low utilization of public EV charging stations is a problem in countries such as the Republic of Korea and China [14], [15], [16].

In the Republic of Korea, the installation of EV chargers is mandatory for apartments with more than 100 units and facilities with more than 50 parking spaces. For new facilities, EV chargers must be installed in 5% of all parking spaces, and for existing facilities, 2% of all parking spaces. Regulations on the number of fast EV chargers vary by county (in Seoul, 10% of all EV chargers must be fast EV chargers). Thus, the uniform mandatory installation of EV chargers has resulted in low utilization rates at facilities where the actual demand for EV charging is low, and congestion due to excessive demand at facilities where the demand for EV charging is high [17].

This paper addresses these issues by analyzing the charging history of EV charging stations across the country installed as of 2022 and their relationship with socioeconomic factors. Based on the analysis, this paper proposes a methodology to prioritize EV charging station installation subsidies for facilities that meet the current EV charging station installation regulations in the Republic of Korea.

TABLE 1. Factors that affect the amount of charging energy by country.

Country	Factors
US [22]	Purpose of the facility, presence of charging fees, population density, number of EVs per thousand people
Switzerland [18]	Population density, number of vehicles, population by age group, percentage of employed, income level
United Kingdom [23]	Points of interest, travel flow, population density
Netherlands [19, 21]	Income level, density of vehicle
France [20]	Traffic convenience

B. PREVIOUS STUDIES

This study analyzed the factors that affect the amount of charging energy at EV charging stations and used the results to prioritize the installation of EV charging stations. Identifying the main factors that affect the amount of charging energy for EVs before optimization is essential because it is not possible to analyze all socioeconomic factors. Many studies have examined the factors that affect the amount of charging energy of EV charging stations.

The factors affecting the amount of charging energy for EVs in the US were segmented and correlated [17]: the purpose of the facility, the presence of charging fees, the population density, and the number of EVs per thousand people. Gellrich et al. [18] examined the factors affecting the amount of charging energy for EVs in Switzerland: population density, number of vehicles (EVs, cars, and PEVs) per thousand people, population by age group, percentage use in the total population, and income level. An analysis of EV charging energy in London was conducted [19], which found that the points of interest, travel flow, and population density significantly affect EV charging energy. Straka et al. [19] analyzed the factors influencing the number of transactions at EV charging stations in the Netherlands. They reported that it is vital to locate EV charging stations in places where people with high-income levels live and that the number of vehicles per square kilometer is important. Wu et al. [20] examined the factors influencing the location of EV charging stations in France. The influencing factors included charging demand, operating economy, traffic convenience, grid security, and construction feasibility [21]. They reported that the charging demand and traffic convenience are the most important factors. Van Montfort et al. [21] confirmed the importance of income level on the amount of charging energy at EV charging stations using charging histories of EV charging stations in The Hague, Netherlands. Table 1 lists the socioeconomic factors analyzed as affecting the amount of charging energy by country.

These studies [18], [19], [20], [21], [22], [23] provide insight into what factors should be analyzed to predict the amount of charging energy required at EV charging stations, but they do not optimize for the actual location of EV charging stations. Therefore, a review of previous studies analyzing the location of EV charging stations was conducted to prioritize the installation of EV charging stations. Considerable research is currently being done to characterize the location of EV charging stations and use this to determine where they should be located.

One of the main methods used to determine the location of EV charging stations is to determine the charging demand based on the driving characteristics of EVs and the location of EV charging stations. Tu et al. [24] and Li et al. [25] identified the location with the highest charging demand for electric taxis. They used it to locate EV charging stations based on the driving data of real electric taxis. Yang et al. [15] analyzed the charging patterns of actual electric taxis to identify charging stations with high charging demand. They reported that charging stations with high charging demand are facilities where vehicles stay for a long time. Therefore, the location of EV charging stations was determined by considering the length of time that the vehicles stayed. Chung and Kwon [26] calculated the actual driving volume of Korean highways, and EV charging stations were installed at high-traffic points. On the other hand, they could not analyze the actual charging energy of EVs, but only the location of EV charging stations on highways. Although Chung and Kwon [26] did not analyze the actual amount of charging energy, it would be effective in analyzing the traffic volume when determining the location of EV charging stations on highways. Gong et al. [27] predicted the amount of charging energy by region using traffic volume, peak traffic, traffic congestion, and vehicle mileage throughout the day. They determined the location of EV charging stations based on the predicted charging demand. Wang et al. [28] predicted the amount of charging energy using the driving patterns of vehicles. They determined the location of EV charging stations based on the installation cost of EV charging stations. Zhao et al. [29] used a recurrent neural network to predict the amount of charging energy at fast EV charging stations based on the driving patterns of EV owners to optimize the location of fast EV charging stations. Their assumption [29] was that EV owners are more likely to charge their EVs as the remaining battery capacity decreases. These studies analyzed the amount of EV charging energy through vehicle driving patterns. Nevertheless, the driving patterns and EV charging patterns may differ. Hence, other factors may affect the amount of charging energy.

Recently, many studies have optimized the location of EV charging stations by identifying the factors that may affect charging other than just traffic patterns. For example, Liu et al. [30] used land values, traffic, and population to analyze EV charging and optimize the location of EV charging stations in Haikou, China, based on the amount of charging energy. Arya and Sridhar [31] optimized the location of EV charging stations in Bangalore, India, by considering traffic data and the purpose of nearby facilities. Erbaş et al. [32] optimized the location of EV charging stations in Istanbul, Turkey, using nearby facilities, land value, number of EVs, and population. Lou et al. [33] used the number of EVs, construction cost, and population to optimize the location of EV charging stations in Seoul, Republic of Korea. Zhang and Iman [34] optimized the location of EV charging stations in the Wasatch Front of Utah, USA, based on sustainability. This sustainability was analyzed based on facility use, land use (e.g., rivers and farmland), future population projections, and travel destinations. Charly et al. [35] optimized the location of EV charging stations in Dublin, Ireland, by considering the parking space, lamp posts, population density, housing, roads, amenities, place of work or study, and distance between EV charging stations.

He et al. [36] surveyed people in Beijing, China, to understand the demand for EVs. They reported that profit and number of vehicles were the most important factors. Based on these results, the location of EV charging stations in Beijing, China, was optimized. Loni and Asadi [37] optimized the location of EV charging stations by analyzing the factors to ensure the accessibility of EV charging infrastructure, charging station construction costs, and actual charging demand data in San Francisco, USA. Table 2 lists the methodologies used by previous studies to optimize the location of EV charging stations.

TABLE 2. EV charging station location optimization methodologies.

Methodology	Description
Driving characteristics of EVs	Using electric taxi driving patterns ([15, 24, 25]). Using highways traffic volume ([26]) Using driving patterns ([27-29])
Using various factors	Using population ([30], [32-35], [37]) Using number of registered EVs ([32, 33], [36]) Using traffic volume ([30], [31], [37]) Using land value or income level ([30], [32], [36, 37]). Purpose of the facility or land ([31, 34, 35]) Construction expense ([33], [37])

Previous studies have recognized the impact of the purpose of the facility on the amount of charging energy and used it for optimization but have been unable to quantitatively show the variation of factors affecting the amount of charging energy based on the purpose of the facility. Therefore, before prioritizing the deployment of EV charging stations, this study will quantitatively show how the factors that affect the amount of charging energy vary depending on the purpose of the facility.

Beyond quantitative analysis, there may be a gap between previous studies and the real world. Previous studies have optimized the location of EV charging stations in a relatively small area (specific cities). For example, these previous studies used only one specific region (usually urban centers) as a case study, so the impact of each factor on EV charging may be unique to that region. Nevertheless, this may be a special phenomenon of that area, and different phenomena can occur in other areas. In addition, the amount of EV charging energy in previous studies is a prediction, and no comparison with actual charging data across the country has been conducted (e.g., South Korea).

This study examined the impact of various factors on EV charging across the region, which will prioritize EV charging station locations to reduce the research gap mentioned above. An analysis of case studies showed that the main factors used in this paper to ensure the accessibility of EV charging infrastructure were income level, education level, race, population, and transportation index.

C. CONTRIBUTIONS AND APPLICATIONS

This study used the actual charging data of EV charging stations in the Republic of Korea to analyze the factors affecting EV charging and their degree through correlation analysis and suggested which EV charging stations should be installed first based on the analysis results.

Simple method for optimizing charging stations. The correlation analysis and optimization method used in this paper were relatively simple compared to the optimization methods used in previous studies (such as predicting driving patterns and considering costs) because the four most important factors, which are also readily available from various socioeconomic factors, were used. Therefore, it is advantageous to use it in policy.

Quantitative insight into the key drivers of charging energy at EV charging stations. The methods proposed in this paper provide quantitative insight into the impact of each factor on the amount of charging energy from an EV charging station, depending on the purpose of the facility where the EV charging station is deployed. In this study, *the amount of charging energy* is the total amount of charging energy provided annually by each EV charging station.

Detailed analysis of EV charging stations. The method proposed in this paper can identify the characteristics of EV charging according to each factor, and the characteristics of EV charging can provide insights into where EV charging stations should be prioritized for deployment.

Application. The key factors used in this paper can prioritize the deployment of EV charging stations in another country because the EV charging pattern of people is similar. In addition, the charging patterns and characteristics observed in this paper on EV charging stations across the country (e.g., South Korea) can increase the utilization rate of the EV charging infrastructure by upgrading the frequently used EV charging stations to install more chargers and removing or converting infrequently used EV charging stations to other uses, which can help improve the EV charging infrastructure in South Korea and extend it to other countries.

The remainder of this paper is organized as follows. Section II provides the background necessary to understand this paper. Section III describes the methodology used to prioritize the deployment of EV charging stations. Section IV validates the proposed methodology. Section V outlines a real-world case study where EV charging stations were prioritized for deployment. Section VI presents the discussion, and Section VII reports the conclusions.

II. BACKGROUND

This section provides the background necessary to prioritize the deployment of EV charging stations.

A. CORRELATION ANALYSIS

The relationship between socioeconomic factors and the amount of charging energy needs to be considered when analyzing the socioeconomic factors that affect the amount of charging energy. This paper used the Pearson's correlation coefficient to determine the correlation. The Pearson's correlation coefficient is a coefficient that measures the linear correlation relationship between two factors. The result is a value from −1 to 1, with values closer to 1 and −1 indicating a positive and negative linear relationship, respectively. The Pearson's correlation is expressed as follows (1) [38], [39].

$$\gamma(x, y) = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \overline{X})^2} \sqrt{\sum_{i=1}^{n} (Y_i - \overline{Y})^2}} \quad (1)$$

where n is the number of samples (in this paper, EV charging stations). X is a socioeconomic factor, and Y is the amount of charging energy of the EV charging station. X_i and Y_i are the values of the i^{th} EV charging station. $\bar{X}$ and $\bar{Y}$ are the average values of X and Y. This expression was used to analyze the correlation between the amount of charging energy at EV charging stations and socioeconomic factors.

B. CONCEPT OF EV CHARGING STATION

In this paper, a fast EV charger is an EV charger with a charging capacity of 50 kWh or more (this criterion is based on the division of fast and slow EV chargers in the Republic of Korea [10]). A slow EV charger is an EV charger with a charging capacity of less than 50 kWh.

An EV charging station is a facility where one or more EV chargers are installed. This concept includes EV chargers. Fig. 1 presents a conceptual diagram showing the relationship between EV charging stations and EV chargers, where EV charging stations are deployed in the parking lot of a facility, and an EV charging station contains one or more EV chargers.

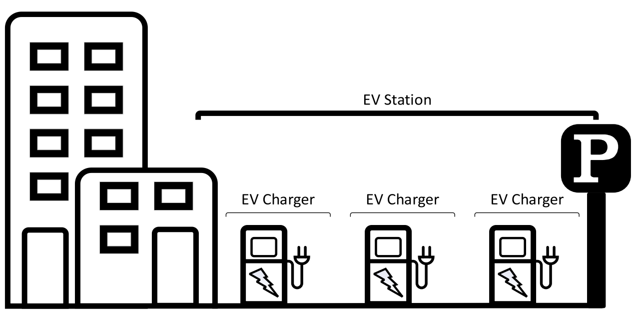

FIGURE 1. Conceptual diagram showing the difference between EV charging stations and EV chargers.

The reason for using the concept of an EV charging station in this paper and distinguishing it from the concept of an EV charger is to reduce the impact of other EV chargers when analyzing the amount of charging energy at an EV charging station. When EV chargers are clustered, the amount of EV charging energy at each EV charger is reduced by the neighboring EV chargers. This may adversely affect the process of analyzing the factors that affect the amount of EV charging energy. Therefore, in this paper, the correlation between the amount of charging energy of EVs and socioeconomic factors is the concept of including EV chargers to reduce the impact of other EV chargers and prioritizing the location of EV charging stations through the analyzed correlation.

III. METHODOLOGY

This section describes the algorithms and factors used to prioritize the deployment of EV charging stations.

A. KEY FACTORS

Many socioeconomic factors play a role, so it is important to determine which ones should be analyzed to prioritize the location of EV charging stations. This study examined the key factors, including the population (population within a radius of approximately 914 m) ([18], [22], [23], [30], [32], [33], [34], [35], [37]), the number of registered EVs ([18], [22], [19], [20], [32], [33], and [36]), traffic volume ([23], [30], [31], [37]), and land value, which can approximate income level (land value within a radius of approximately 914 m) ([18], [19], [20], [21], [30], [32], [37]).

The key factors were selected for three reasons. 1) Previous research has shown that these particular factors are often used to optimize the location of EV charging stations. 2) The accessibility of these factors as public data makes them a practical choice for a global model. 3) The factors are inherently straightforward, providing direct and immediate insight into the level of charging energy demand. For example, a higher population intuitively suggests an increased amount of charging energy needed, a clear and simple relationship that does not require complex interpretation. This simplicity is critical to formulating an intuitive and easily communicable EV charging deployment strategy.

These factors are described in more detail in the following sections. The correlations were analyzed according to the purpose of the facility (residential facilities, commercial facilities, corporate facilities, public institution facilities, public parking lots, and other facilities).

1) PURPOSE OF FACILITY

In this study, correlation analysis was conducted separately based on the purpose of the facility. Correlation analysis was conducted separately because the factors affecting the amount of charging energy differ. For example, the factors affecting the amount of charging energy for an EV in a commercial facility may differ from those affecting the amount of charging energy for an EV in a residential facility (e.g., apartments are a common residential facility in the Republic of Korea). Therefore, correlation analysis was conducted by categorizing the purpose of the facility into six types: residential facilities, commercial facilities, corporate facilities, public institution facilities, public parking lots, and other facilities. Table 3 provides a description and example of the purpose of each facility.

TABLE 3. Purpose of the facility.

Purpose of Facility	Description	Example
Residential [a]	Public housing that houses several families.	Apartments
Commercial	Facility used for commercial purposes.	Department stores, hotels, restaurants, gas stations, etc.
Corporate	Facility, such as a company, where people work.	Workplace, office building, etc.
Public institution	Government facility that may be a workplace for specific people.	Government offices, community centers, etc.
Public parking lots	Public parking lots available to an unspecified number of people.	Public parking lots
Others	Other remaining uncategorized facilities	Educational facilities, vehicle maintenance centers, tourist attractions, etc.

[a]Owing to privacy issues, EV charging stations in single-family homes were not surveyed. On the other hand, there is no obligation to install EV charging stations in private residential facilities, and the percentage of single-family homes in the Republic of Korea is approximately 13.71% [40], so it is unlikely to have a significant impact on the analysis.

2) POPULATION

The number of people around an EV charging station is one of the factors that previous studies used to predict the amount of charging energy at EV charging stations. It is an important factor in prioritizing the deployment of EV charging stations. Therefore, this study used the population as a critical factor.

There are several criteria for population. Population can be the number of people in the county where the EV charging station is located or the number of people within a certain distance from the EV charging station. In this study, the key factor was the number of people within a 914 m (=3000 ft) radius of an EV charging station. This reflects the maximum distance people are willing to walk [41]. Therefore, the number of people within 914 m is the key factor in this paper.

Population data in the Republic of Korea is available in a 100 m by 100 m grid from the Korean Statistical Information Service (KOSIS). This grid-based population data provides a detailed analysis of the population distribution by region and is an important basis for spatial analysis.

Fig. 2 shows the method used to collect population data. A circle with a radius of 914 m was drawn around the EV charging station, and all 100 m × 100 m grids tangent to or in the circle were selected. The population of all 100 m × 100 m grids was then summed. This sum is the key factor used in this paper.

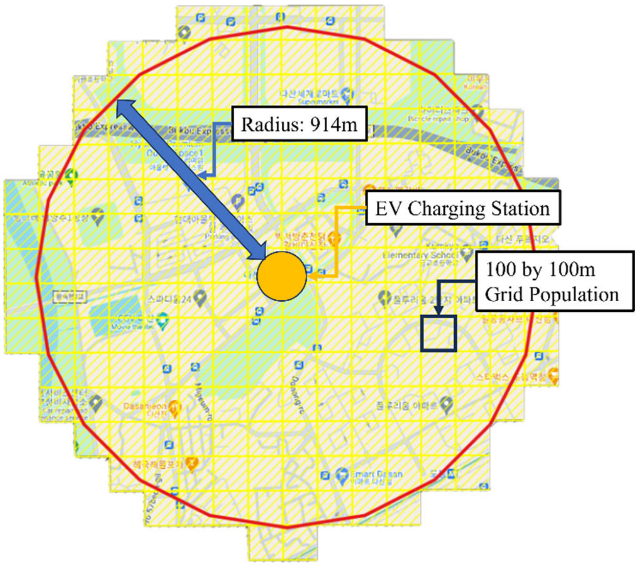

FIGURE 2. Methods for collecting population data.

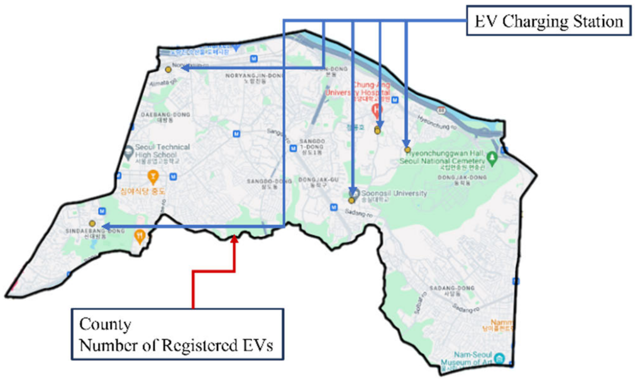

FIGURE 3. Methods for collecting the number of registered EVs.

3) NUMBER OF REGISTERED ELECTRIC VEHICLES

The number of registered EVs around an EV charging station is one of the factors that previous studies have used to predict the amount of charging energy at EV charging stations. It is an important factor when prioritizing the deployment of EV charging stations. Therefore, this study used the number of registered EVs as a critical factor.

Data on the number of registered EVs are only available by county, which contrasts with the granularity of the population data, which is disaggregated into 100 m × 100 m grids. Therefore, this study analyzed the correlation between the number of registered EVs in the county where an EV charging station was located and the amount of charging energy at that EV charging station. The number of registered EVs in the Republic of Korea is available from the KOSIS. Fig. 3 outlines the method used to collect the number of registered EVs data. For example, the EV charging stations shown in Fig. 3 are all located in the same county, so they all have the same number of registered EVs.

4) TRAFFIC VOLUME

The traffic volume at an EV charging station is one of the factors used in previous studies to predict the amount of charging

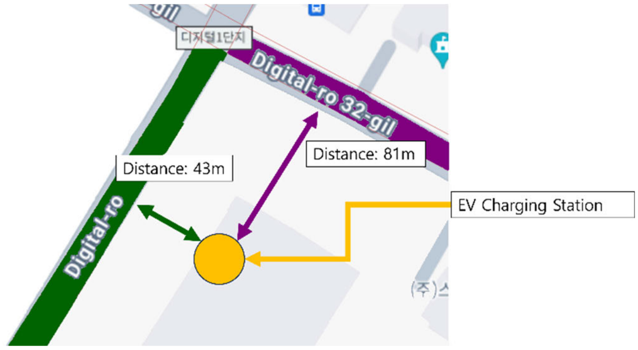

FIGURE 4. Method for collecting the traffic volumes.

energy at EV charging stations. This value is an important factor in prioritizing the deployment of EV charging stations. Therefore, this study used traffic volume as a key factor.

Traffic volume data is provided on a road-by-road basis. Therefore, this study used the traffic volume of the road closest to the EV charging station. The traffic volume uses the annual average daily traffic (AADT) as a key factor. Data on AADT by road was provided by View-T, a service provided by the Korea transportation database (KTDB).

Fig. 4 outlines how the AADT was collected. The distance between the green road (Digital-ro) and the EV charging station was 43 m. The green road was closer to the EV charging station than the purple road (Digitoal-ro 32-gil). Therefore, the AADT of the green road was used as the key factor for the EV charging station in Fig. 4.

5) LAND VALUE

The land value around an EV charging station is one of the factors that previous studies have used to predict the amount of charging energy at EV charging stations. This is an important factor in prioritizing the deployment of EV charging stations. Therefore, this paper used the land value as a key factor.

The land value was determined as the average of land prices (KRW/m^2) within a 914 m radius. This reflects the maximum distance people are willing to walk [41]. Therefore, land value within 914 m is a key factor in this study.

Land value data in the Republic of Korea is available for each land parcel from the Ministry of Land, Infrastructure and Transport (MOLIT). Fig. 5 shows the method used to collect land value data. A circle with a radius of 914 m was drawn around the EV charging station, and all land tangent to or contained by the circle was selected. The land value of all the land was then averaged and used as a key factor.

6) SUMMARY OF THE KEY FACTORS

As a result of case studies, this study used the main four factors from various socioeconomic factors; the detailed analysis results are presented in the following case study section. For each EV charging station, each key factor (population, number of registered EVs, traffic volume, and land value)

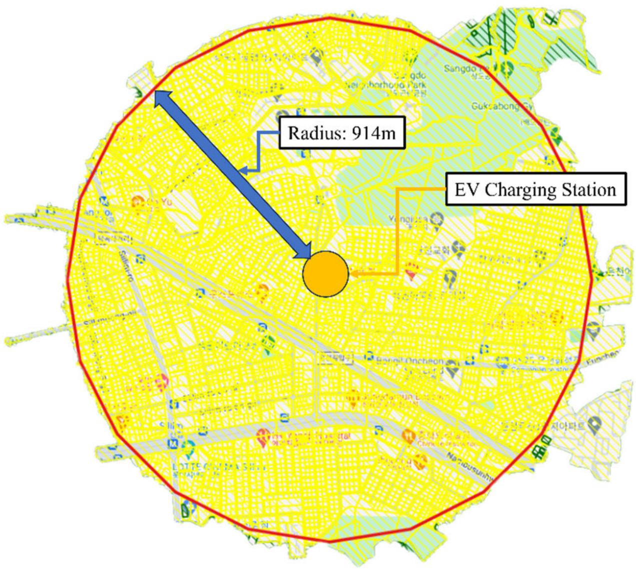

FIGURE 5. Methods for collecting the land value data.

TABLE 4. Summary of the key factors for EV charging station analysis.

Key Factor	Description
Population	The number of residents within 914 m of the EV charging station.
Number of EVs	Number of registered EVs in the county with EV charging stations.
Traffic volume	AADT on the road closest to the location of the EV charging station.
Land value	Average land value within 914m of the EV charging station.

was spatially combined and compared with the amount of charging energy. Table 4 summarizes each key factor.

B. GENETIC ALGORITHM

A genetic algorithm was used to optimize the location of the electric vehicle charging stations. A genetic algorithm is an optimization technique developed by John Holland [42] based on natural evolutionary methods. It passes the genes of the parents to their children but crosses the genes of each parent so that the children have different combinations of genes (a combination of genes is defined as a population). The genes of the child with the best combination of genes are then crossed and passed on to a new child. This study defined the sum of the normalized product of key factors and weights as the total score. In the genetic algorithm, the parent and child are the correlation coefficients between the total score and the amount of charging energy. A gene is a weight for each key factor. Therefore, among the children with different weight combinations, the children with the highest correlation between the total score and the amount of charging energy were selected. These selected children are defined as the elite children. Based on the weights of these elite children, another weight combination was formed, and the correlation between the total score and the amount of charging energy was analyzed. Repeating this process is the genetic algorithm shown in Fig. 6. The detailed parameters used in this genetic algorithm (e.g., number of children selected, number of generations, and population size) are shown in the Appendix.

In this figure, $W1_1$, $W1_2$, $W1_3$, and $W1_4$ are the genes (weights) of Parent 1. $W2_1$, $W2_2$, $W2_3$, and $W2_4$ are the genes (weights) of Parent 2. When iterating, the optimal solution is determined by the values of the first generation, as shown in Fig. 6, which means that the optimal solution can be missed because the results cannot be obtained by new genes (weights) other than those of the first generation. Therefore, the genetic algorithm adds mutations. A mutation is a gene absent in the parent's genes that is present in the child. Fig. 7 illustrates a mutation.

In Fig. 7, $W1_1$, $W1_2$, $W1_3$, and $W1_4$ are the genes (weights) of Parent 1. $W2_1$, $W2_2$, $W2_3$, and $W2_4$ are the genes (weights) of parent 2. $W2_5$ is a new gene (weight) created by a mutation. This process of creating mutations allows users to explore new genes. Exploring new genes can improve the performance of the genetic algorithm.

Genetic algorithms are appropriate for this study because: 1) The solution space is very complex because there are many variables to consider, such as multiple purposes of the facility and different key factors. Genetic algorithms can flexibly explore the global optimal solution in such multivariate optimization problems. 2) It can solve local optimization problems. Genetic algorithms can solve local optimization problems through stochastic exploration. 3) Although the constraints in this model are clearly defined, it is difficult to mathematically formalize the optimal solution that satisfies them. Genetic algorithms have an advantage in solving such nonlinear optimization problems through iterative exploration.

C. DATA COLLECTION AND ANALYSIS PROCESS

In this study, data were collected using an application programming interface (API) and geographic information system (GIS), and data analysis and algorithm development were performed using MATLAB, QGIS, and EXCELL.

1) DATA COLLECTION PROCESS

The data used in this paper were obtained from charging point operators (CPOs), who provided the charging history of EV charging stations and EV charging station data (including the purpose of the facility where the EV charging station is installed and the capacity of the EV charging station). Population data, number of registered EVs, traffic volume data, and land value data were obtained from public data garnered through API and GIS. Fig. 8 presents the data collection process.

2) DATA ANALYSIS PROCESS

Data analysis in this paper was performed using MATLAB, QGIS, and EXCELL. The correlations were analyzed based on data collected throughout the Republic of Korea. After

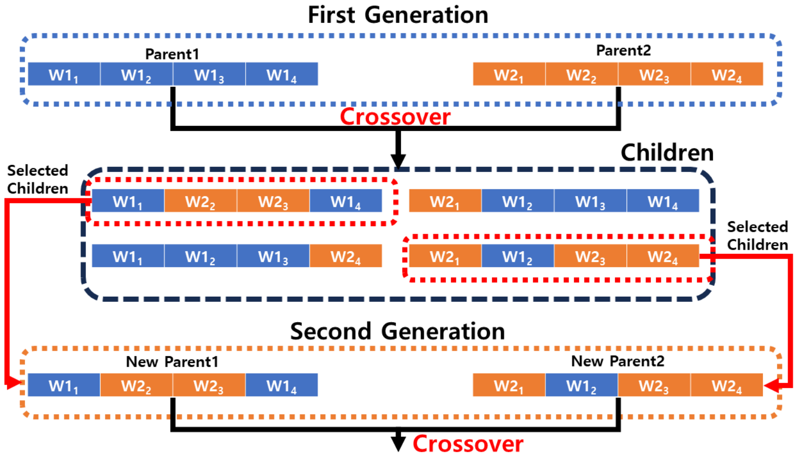

FIGURE 6. Basic genetic algorithm process.

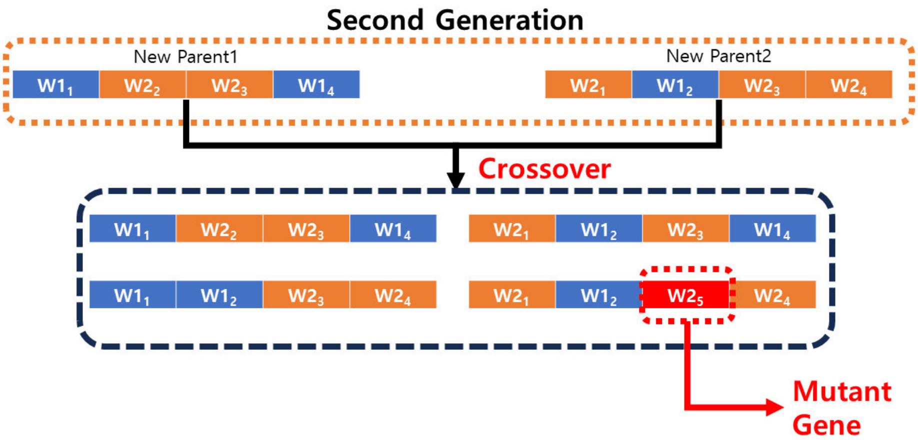

FIGURE 7. Mutant process in a genetic algorithm.

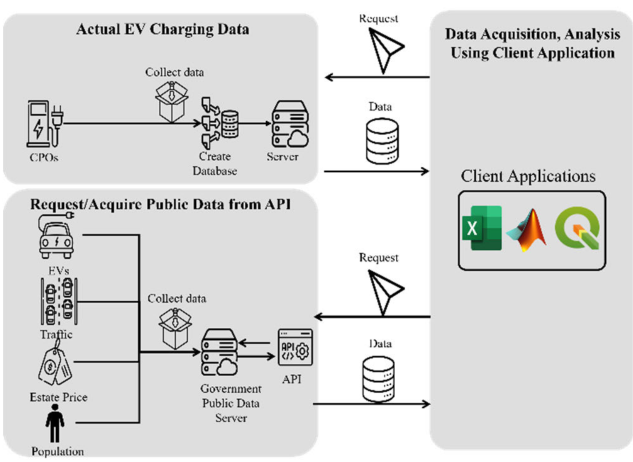

FIGURE 8. Data collection process.

correlation analysis, each key factor (population, number of registered EVs, traffic volume, and land value) was normalized using Equation (2). After normalization, scoring was performed by the sum of each normalized key factor. Finally, the total score was correlated with the amount of charging energy at EV charging stations. The genetic algorithm applies a weight to each key factor to increase the correlation between the total score and the amount of charging energy at the EV charging station and finds the optimal weight.

$$F_{ij-norm} = \frac{F_{ij} - F_{i-\min}}{F_{i-\max} - F_{i-\min}} \tag{2}$$

where F represents the key factor; i is the number of key factors representing the population, number of registered EVs, traffic volume, and land value. $F_{i-\max}$ and $F_{i-\min}$ are the maximum and minimum values of the i^{th} key factor, respectively. j is the number of EV charging stations collected. F_{ij} is the value of the i^{th} key factor at the j^{th} EV charging station. $F_{ij-norm}$ is the resulting value when the value of the i^{th} key factor at the j^{th} EV charging station is normalized. In this case, the right side of the expression is multiplied by 100 to ensure that the maximum value of $F_{ij-norm}$ is 100.

After finding the optimal weights, the key factors are collected around the facilities that meet the regulations for

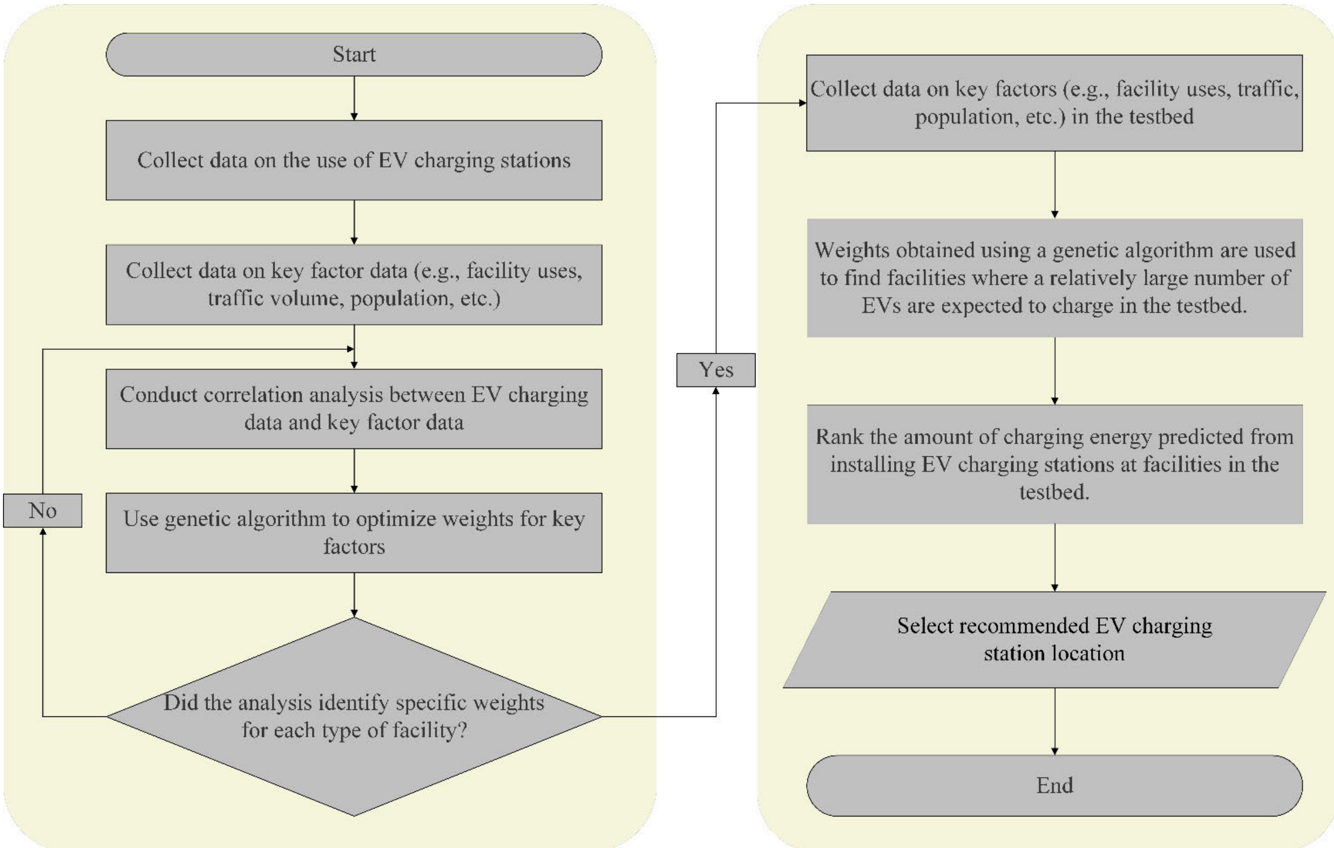

FIGURE 9. Data analysis process flowchart.

installing EV charging stations in the test bed (in the Republic of Korea, the parking lot size is at least 50 spaces). The facilities predicted to have a high amount of EV charging energy are ranked by applying the optimal weights to the collected key factors. The EV charging stations to be installed each year were selected (the number of charging stations to be installed is based on the EV charging station installation target of the Republic of Korea). Fig. 9 presents a flowchart of this process.

IV. VALIDATION

This section validates the proposed methodology. First, this section validates the key factors. Second, this section validates the optimal selection method of EV charging stations using the four key factors and the optimal weighting factors of different facilities and charger types.

Table 5 summarizes the characteristics, such as the charger type and number of EVs in the Republic of Korea (in 2022).

With a world average of 10 EV/EV charger [11], the Republic of Korea has a large number of EV chargers.

A. FOUR KEY FACTORS

This paper validates the four key factors by comparing the correlation coefficients of the key factors with the charging history in South Korea. The EV charging stations in operation in 2022 were analyzed according to the facility purpose.

TABLE 5. Characteristics of the republic of Korea in 2022.

Characteristic	Value	Description
EV/Total vehicles	1.24%	Number of EVs in the Republic of Korea: 315,535 Number of vehicles in the Republic of Korea: 25,503,078
EV/Fast EV charger	15.29	Number of fast EV chargers in the Republic of Korea: 20,641
EV/Slow EV charger	1.82	Number of fast EV chargers in the Republic of Korea: 173,440
EV/EV charger	1.63	Number of EV chargers in the Republic of Korea: 194,081

Table 6 lists the number of fast EV charging stations and fast EV chargers per facility purpose in the Republic of Korea. Table 7 presents the number of slow EV charging stations and slow EV chargers per facility purpose in the Republic of Korea. Table 8 presents the correlation between each key factor and the amount of charging energy per fast EV charging station per facility purpose.

In residential facilities, slow EV charging stations are most affected by the number of EVs. Since most EV charging stations installed in residential facilities are slow EV charging stations, it can be seen that it is best to install EV charging stations in residential facilities based on the number of EVs in a residential facility.

TABLE 6. Number of fast EV chargers and fast EV charging stations (in the republic of Korea in 2022).

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	125	92
Commercial	1511	683
Corporate	235	100
Public institution	3385	2108
Public parking lots	1989	1245
Others	2839	1541

TABLE 7. Number of slow EV chargers and slow EV charging stations (in the republic of Korea in 2022).

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	39693	7134
Commercial	2417	861
Corporate	1865	509
Public institution	2457	1193
Public parking lots	372	106
Others	3132	1091

For slow and fast EV charging stations in commercial facilities, the amount of charging energy is influenced mainly by land value and traffic volume. This is because income and education levels are positively correlated with the number of registered EVs [43]. In addition, high traffic volume means there are many visitors to a commercial facility, hence many EV users. As a result, commercial facilities in relatively affluent areas with many visitors are expected to have many EV users. Therefore, when installing EV charging stations in commercial facilities, it is necessary to install more EV charging stations in commercial facilities (such as department stores) that are used mainly by people with relatively high incomes.

For corporates, there are no key factors that are particularly highly correlated. This is probably because corporations are not accessible to outsiders and tend to be characterized by the characteristics of the company's employees. Therefore, when installing EV charging stations in corporations, it is recommended that the number of EVs owned by the employees be investigated, and EV charging stations should be installed accordingly.

Public institutions (both slow EV stations and fast EV stations) are most affected by population and traffic volume, suggesting that more EV charging stations should be installed in populated areas, especially in high-traffic areas.

For public parking lots, fast EV charging stations are most affected by the population and traffic volume, while slow EV charging stations are most affected by the population and the number of registered EVs. This is likely because, for fast EV charging stations, when EV users need to charge their EVs, they use the fast EV charging stations in public parking lots that are also available to outsiders. Slow EV charging stations are affected by the population and the number of registered EVs because there is a shortage of parking spaces in the Republic of Korea, so EV users charge their EVs in public parking lots rather than at their residences [44].

B. OPTIMIZATION

1) OPTIMAL WEIGHTS

This study optimizes EV charging stations using the four key factors and optimal weighting factors of different facility and charger types. The weights for each facility and charger type were determined using the correlation coefficients of the key factors, such as population, number of EVs, traffic volume, land value, and a genetic algorithm. The genetic algorithm found the optimized values according to Equation (3), and the constraint was calculated using Equations (4) – (5). Table 9 lists the results of the optimal weights.

$$J_k = \max(corr(\sum_{i=1}^{n}(W_i \times F_i))) \tag{3}$$

$$-10 \leq W_i \leq 10 \tag{4}$$

$$10 = \sum_{i=1}^{n} W_i \tag{5}$$

where J is the objective function to be maximized; k is the number of purposes of the facilities (e.g., $k = 6$ for residential, commercial, corporate, public institution, public parking, and others); $corr$ is to calculate the correlation coefficient. W represents the weights; F represents the key factors; n is the number of key factors (e.g., $n = 4$ for population, number of EVs, traffic volume, land value).

A correlation coefficient of 0.2 or higher indicates a weak correlation, while a correlation coefficient of 0.4 or higher indicates a medium correlation [45]. After optimization, except for slow EV charging stations in residential and public institutions, the correlation coefficient was above 0.2, indicating a weak correlation. In particular, the correlation coefficient for slow EV charging stations in commercial and public parking lots was medium. The weights obtained from Table 9 were applied to the key factors in the testbed, such as an urban area (Seoul), a tourist area (Jeju Island), and a rural area (Gangwon Province). In this case, the key factors were collected from facilities obligated to deploy EV charging stations in the Republic of Korea (facilities with more than 50 parking spaces).

2) VALIDATION USING CORRELATION COEFFICIENTS

This section validates the methodology presented in this paper by comparing the correlation coefficient between the predicted charge energy and the actual charge energy. Three scenarios were created to validate the methodology. The first scenario was an unweighted method, defined as scenario-no weight. The second scenario was a scenario with different weights for each facility used regardless of the type of EV charging station, defined as scenario-facility. The third

TABLE 8. Correlation coefficient according to the EV charger speed and facility purpose (in the republic of Korea in 2022).

Type	Purpose of Facility	Population	Number of EVs	Traffic Volume	Land Value
Fast	Residential	− 0.2004	0.2822	− 0.1522	− 0.1752
	Commercial	0.1924	− 0.1319	0.3287	0.2055
	Corporate	0.1339	− 0.0250	− 0.0447	0.1024
	Public institution	0.3200	0.0921	0.1928	0.1139
	Public parking lots	0.1335	0.0277	0.1027	0.0673
	Others	0.1100	− 0.0378	0.0711	0.0293
Slow	Residential	− 0.0157	0.0358	− 0.0141	− 0.0528
	Commercial	0.0693	0.0948	0.0828	0.1994
	Corporate	− 0.0397	0.0180	− 0.0532	− 0.0665
	Public institution	0.2580	− 0.0173	0.1129	0.0675
	Public parking lots	0.0801	0.2686	0.0336	− 0.0089
	Others	− 0.0244	0.0637	0.0224	− 0.0324

TABLE 9. Optimized weights and correlation analysis for EV charging facilities according to the type and purpose.

Type	Purpose of Facility	Population (weight)	Number. of EVs (weight)	Traffic Volume (weight)	Land Value (weight)	Total Score (correlation coefficient)
Fast	Residential	−1.2167	10.0000	−2.5982	3.8149	0.2910
	Commercial	1.7682	−0.6450	2.5159	6.3069	0.3798
	Corporate	4.7746	5.9960	0.7351	−0.15055	0.2159
	Public institution	5.7787	4.1661	1.4234	−1.3680	0.3900
	Public parking lots	1.9788	2.3856	1.7930	3.8426	0.2912
	Others	5.1968	2.1115	9.9652	−7.2735	0.1726
Slow	Residential	10.0000	−8.1501	10.0000	−1.8509	0.0392
	Commercial	−1.0883	0.1340	0.9544	10.0000	0.4601
	Corporate	−0.4334	−1.1324	1.5658	10.0000	0.2099
	Public institution	4.8305	3.9239	2.7951	−1.5495	0.1675
	Public parking lots	1.5449	6.2440	0.4232	1.7879	0.5291
	Others	−0.1931	−0.1812	5.5331	4.8411	0.1083

TABLE 10. Comparison of each method of correlation coefficients to actual charge history in 2022.

Type		Scenario–no weight	Scenario–facility	Scenario–type	Scenario-proposed
Fast	Residential	−0.0400	−0.2268	−0.0966	0.2910
	Commercial	0.2514	0.4772	0.3161	0.3798
	Corporate	0.1442	0.1017	0.1246	0.2159
	Public institution	0.2332	0.3503	0.3403	0.3900
	Public parking lots	0.1194	0.0944	0.1114	0.2912
	Others	0.0014	0.1276	0.1124	0.1726
Slow	Residential	−0.0127	0.0186	0.0348	0.0392
	Commercial	0.1811	0.1801	0.1115	0.4601
	Corporate	0.1098	0.1943	0.1118	0.2099
	Public institution	0.1562	0.3018	0.2629	0.1675
	Public parking lots	0.3479	0.3075	0.0489	0.5291
	Others	0.0633	0.1119	0.0890	0.1083

scenario was a scenario with different weights for each type of charger, defined as scenario-type. The weights in the scenario-facility and scenario-type were obtained using the same genetic algorithm used in this study. Table 10 compares the total score in each scenario and its correlation with the amount of charging energy. The weights applied in the scenarios-facility and scenario-type are shown in the APPENDIX.

Table 10 shows the scenario-proposed: the scenario with different weights per facility and per type of EV charging station, which is the main methodology proposed in this paper.

The total score of scenario-proposed had a higher correlation with the amount of charging energy than scenario-facility, except for fast EV charging stations deployed in commercial facilities and slow EV charging stations deployed in public institutions. The total score of scenario-proposed had a higher correlation with the amount of charging energy than scenario-type, except for slow EV charging stations deployed in public institutions. Hence, the method proposed in this paper is relatively more accurate in predicting the amount of charging energy. Further detailed validation and improvement of the genetic algorithm will be addressed in a separate publication.

V. CASE STUDY

This study examined EV charging stations in the Republic of Korea as a case study. Three scenarios (no weighting, different weighting by EV charging station type, and different weighting by the purpose of the facility) were constructed in the previous validation section to test the validity of the methodology used in this paper. The results obtained by the methodology presented in this paper were analyzed by applying it to an urban area (Seoul), a rural area (Gangwon-do), and a tourist area (Jeju Island). The key factors that influenced the amount of charging energy of EV charging stations varied according to the type of EV charging station and the purpose of the facility where the EV charging station was installed. The methodology presented in this paper was more effective for which region (urban area, rural area, and tourist area), which type (fast and slow), and which purpose of the facility (residential, commercial, corporate, public institution, and public parking lot).

The correlation between the total score of EV charging stations located in urban areas (Seoul), rural areas (Gangwon-do), and tourist areas (Jeju Island) and the amount of charging energy was analyzed to verify the effectiveness of the proposed method in this paper. In addition, the currently installed EV charging stations were divided into four tiers based on the performance criteria. Each tier was based on the top 25% of charging station performance: Tiers 1, 2, 3, and 4 were the top 25%, top 25–50%, top 50–75%, and the remaining charging stations, respectively. This tier classifies the urgency of building EV charging stations, prioritizing completion within four years to meet the Republic of Korea's statutory deadline set by the Act to Promote the Development and Distribution of Environment-Friendly Automobiles. The performance of the methodology was evaluated by the percentage of agreement between the tiers based on the actual amount of energy charged and the tiers based on the total score. This is defined as the match rate in the following case studies.

TABLE 11. Number of fast EV chargers and fast EV charging stations in Seoul in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	28	16
Commercial	158	60
Corporate	59	23
Public institution	150	87
Public parking lots	267	152
Others	177	81

TABLE 12. Number of slow EV chargers and slow EV charging stations in Seoul in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	7905	1129
Commercial	238	41
Corporate	670	129
Public institution	362	150
Public parking lots	168	30
Others	497	140

TABLE 13. EV charging station correlation and match rates by facility type (SEOUL) in 2022.

Purpose of Facility	Fast EV Charging Station Evaluation	Slow EV Charging Station Evaluation
Residential	0.4490 [b]	0.0859 [b]
Commercial	0.2083 [b]	0.4857 [b]
Corporate	−0.2540 [b]	0.01672 [b]
Public institution	0.0026[b]	−0.0176 [b]
Public parking lots	0.1322[b]	0.2856 [b]
Others	0.0271[b]	0.0312 [b]
Match rate	30.79%	28.54%

[b]This number shows the correlation coefficient between the total score and the amount of charging energy at the EV charging station.

A. METROPOLITAN AREA (SEOUL)

Tables 11 and 12 list the status of the analyzed EV charging stations and EV chargers among the EV charging stations and EV chargers installed in Seoul. Table 13 lists the results of the methodology evaluation in Seoul. Figs. 10 and 11 present the results of the study. Tier 1 represents facilities that need to deploy EV charging within one year. Tier 4 represents facilities that need to deploy within four years. This categorization places the top 25% of facilities with 50 or more parking spaces in terms of the expected amount of charging energy in Tier 1, the top 25–50% in Tier 2, the top 50–75% in Tier 3, and the rest in Tier 4.

For residential facilities in Seoul, the correlation coefficient between the total score of fast EV charging stations and the amount of charging energy was 0.4490, which was higher than the national average, suggesting that the number of registered EVs and land value have a greater impact on the amount of charging energy at fast EV charging stations in urban residential facilities. For commercial facilities, the

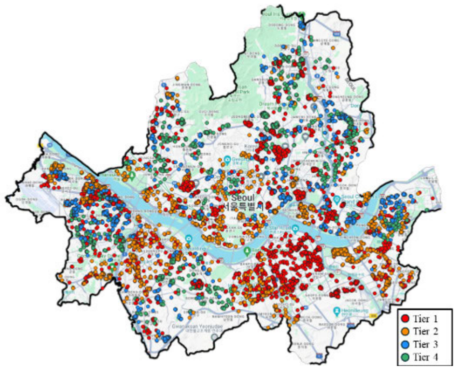

FIGURE 10. Map of priority deployment of fast EV charging stations in Seoul.

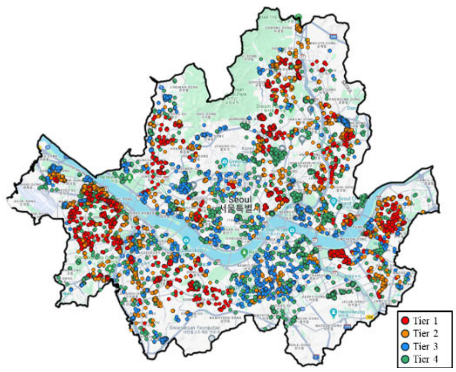

FIGURE 11. Map of priority deployment of slow EV charging stations in Seoul.

correlation coefficient between the total score of the slow EV charging stations and the amount of charging energy was 0.4857, which was also higher than the national average, suggesting that the land value has a greater impact on the amount of charging energy of slow EV charging stations in urban commercial facilities. In contrast, the correlation coefficient for fast EV charging stations at corporate facilities was −0.2540, which is opposite the national average. This may be because difficult-to-analyze factors, such as the number of employees and size of the corporation, are more important to corporations than socioeconomic factors.

The match rate, or accuracy of charge energy prediction, for fast chargers in Seoul in 2022 decreases in the order of residential, commercial, public parking, others, public institutions, and corporations. The match rate for slow chargers decreased in the order of commercial, public parking lots, residential, others, corporate, and public institutions.

The results of EV charging station deployment prioritization showed that in Seoul, fast EV charging stations are prioritized in districts with high populations, income levels, and number of EVs (e.g., Gangnam-gu). On the other hand, slow EV charging stations are prioritized in districts with high population density (e.g., Yangcheon-gu and Dongjak-gu). Based on these results, in urban areas, it is reasonable to prioritize subsidies for fast EV charging stations in distinct areas with high-income levels and a large number of EVs, and to prioritize subsidies for slow EV charging stations in districts with high population densities.

TABLE 14. Number of fast EV chargers and fast EV charging stations in Jeju Island in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	29	21
Commercial	231	126
Corporate	15	6
Public institution	280	152
Public parking lots	170	86
Others	383	212

TABLE 15. Number of slow EV chargers and slow EV charging stations in Jeju Island in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	548	194
Commercial	552	210
Corporate	109	52
Public institution	299	109
Public parking lots	44	7
Others	329	126

TABLE 16. EV charging station correlation and match rates by facility type (in Jeju Island) in 2022.

Purpose of Facility	Fast EV Charging Station Evaluation	Slow EV Charging Station Evaluation
Residential	−0.1610 [c]	−0.0341 [c]
Commercial	0.1825 [c]	0.0620 [c]
Corporate	N/A	−0.0766 [c]
Public institution	0.2963 [c]	0.1222 [c]
Public parking lots	0.2540 [c]	−0.6441 [c]
Others	0.0159 [c]	0.0457 [c]
Match rate	30.82%	28.51%

[c] This number shows the correlation coefficient between the total score and the amount of charging energy at the EV charging station.

B. TOURIST AREA (JEJU ISLAND)

Tables 14 and 15 list the status of the analyzed EV charging stations and EV chargers among the EV charging stations and EV chargers installed in Jeju Island in 2022. Table 16 presents the results of the methodology evaluation in Jeju Island. Figs. 12 and 13 show the results of the study.

The values shown as N/A in Table 16 could not be correlated due to the small sample size.

The analysis results in tourist destinations showed that fast EV charging stations installed in commercial facilities, public institutions, and public parking lots are highly correlated, so it is considered appropriate to use the proposed model for such facilities (commercial, public institutions, and public parking lots) in tourist destinations. That is, fast EV charging stations installed at public institutions in tourist destinations are strongly influenced by the population and the number

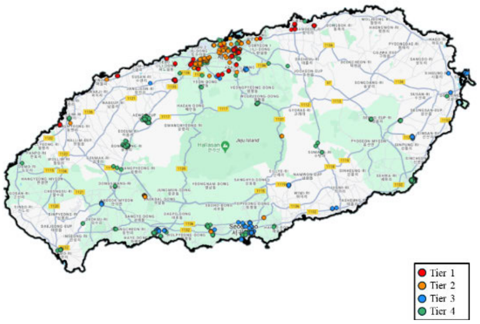

FIGURE 12. Map of priority deployment of fast EV charging stations in Jeju Island.

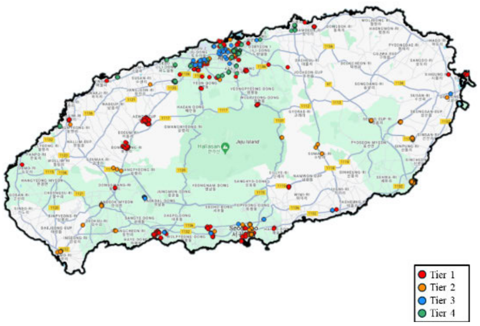

FIGURE 13. Map of priority deployment of slow EV charging stations in Jeju Island.

of registered EVs. Fast EV charging stations installed at public parking lots are equally influenced by the four key factors, and fast EV charging stations installed at commercial facilities are strongly influenced by the land value.

Outside of these facilities, however, there was no clear correlation between the total score and the amount of charging energy, or the correlation was reversed across the nation. This may be due to the specificity of Jeju Island. For example, Jeju Island has a high proportion of rental cars, with approximately 38% of all vehicles being rental cars [46], [47]. The amount of charging energy at EV charging stations in places used by rental car users (who are more likely to be tourists) will also be high because the average daily mileage of rental cars is more than 3.5 times higher than that of regular passenger cars [48], [49]. Therefore, the correlation is not apparent for slow EV charging stations in commercial facilities, which are facilities mainly used by tourists. Therefore, the proportion of rental cars should be considered when applying the Jeju Island results to other tourist areas.

The correlation coefficient between the total number of EV fast charging stations in residential facilities and the amount of charging energy was −0.1610, which is opposite to the national average. Jeju Island has only two counties, so the number of registered EVs is not disaggregated. In addition, the sample size is small at 21, which increased the error due to some outliers. Indeed, the EV fast charger in Jeju Island is an outlier. Although it is located in a public housing facility, it is open for use by public housing residents and outsiders. Hence, there is a relatively large amount of charging energy

TABLE 17. Number of fast EV chargers and fast EV charging stations in Gangwon-do in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	2	1
Commercial	97	49
Corporate	2	1
Public institution	224	137
Public parking lots	114	67
Others	193	94

TABLE 18. Number of slow EV chargers and slow EV charging stations in Gangwon-do in 2022.

Purpose of Facility	Number of EV chargers (EA)	Number of EV charging stations (EA)
Residential	802	128
Commercial	230	86
Corporate	13	8
Public institution	76	57
Public parking lots	1	1
Others	111	42

because these highly unusual cases have a strong influence on the results (the correlation coefficient between the total score and charging energy when the unusual cases are removed was 0.2023).

The correlation coefficient between the total score of slow EV charging stations in public parking lots and the amount of charging energy was −0.6441, which is opposite to the national average, indicating that the number of registered EVs, population, and land value negatively affect the amount of slow charging energy in parking lots in urban areas. Hence, public parking in tourist areas with relatively high charging energy is located in areas with fewer EVs and smaller populations, reducing the correlation between the charging energy and the overall score calculated using the proposed method.

C. RURAL AREA (GANGWON-DO)

Tables 17 and 18 present the status of the analyzed EV charging stations and EV chargers among the EV charging stations and EV chargers installed in Gangwon-do. Table 19 lists the results of the methodology evaluation in Gangwon-do. Figs. 14 and 15 present the results of the study.

The values shown as N/A could not be correlated due to the small sample size.

The correlation coefficient between the total score of slow EV charging stations in residential facilities in Gangwon-do and the amount of charging energy was 0.2150, which is higher than the national average. This suggests that the influence of population and traffic volume on the amount of charging energy in residential facilities in rural areas may be greater than the national average.

In addition to the slow EV charging stations in residential facilities, the correlation between the total score and the

TABLE 19. EV charging station correlation and match rates by facility type (in Gangwon-Do) in 2022.

Purpose of Facility	Fast EV Charging Station Evaluation	Slow EV Charging Station Evaluation
Residential	N/A	0.2150 [d]
Commercial	0.0266 [d]	−0.0608 [d]
Corporate	N/A	0.3533 [d]
Public institution	0.0685 [d]	0.0078 [d]
Public parking lots	0.0320 [d]	N/A
Others	−0.0371 [d]	0.0673 [d]
Match rate	22.48%	34.69%

[d] This number shows the correlation coefficient between the total score and the amount of charging energy at the EV charging station.

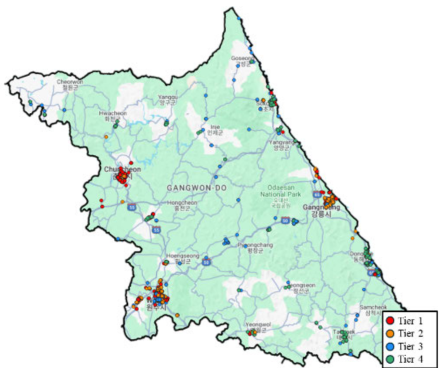

FIGURE 14. Map of priority deployment of fast EV charging stations in Gangwon-Do.

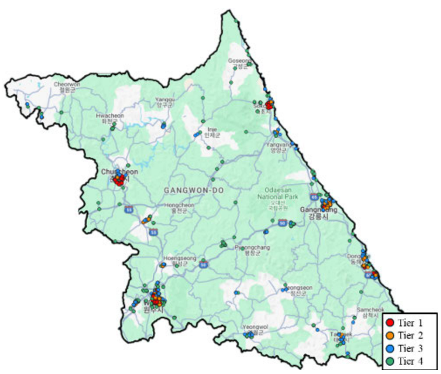

FIGURE 15. Map of priority deployment of slow EV charging stations in Gangwon-Do.

amount of charging energy was low. This may be due to the high dispersion of socioeconomic factors in rural areas. Therefore, it is necessary to analyze the area in more detail in the future (currently, it is impossible to analyze it in more detail due to the small number of EV charging stations deployed).

As a result of prioritizing the deployment of EV charging stations, it was found that in Gangwon-do, fast EV charging stations and slow EV charging stations are deployed mainly due to the city's policy. Based on these results, it is considered appropriate to prioritize subsidies for EV charging stations deployed downtown in rural areas after segmenting the regions.

TABLE 20. Genetic algorithm parameter value.

Parameter	Value (EA)
Population	50
Max generation	200
Elite children	3

VI. DISCUSSION

In this study, the correlation between the total score and the amount of charging energy was considered significant if the correlation coefficient was 0.2 or higher. Therefore, it was determined that only facilities (fast or slow or both) with a correlation coefficient of 0.2 or higher between the total score of the model used in this study and the charging energy can be prioritized for EV charging station installation.

Urban areas in South Korea. In urban areas, it was found that through the methodology in this paper, it is possible to prioritize the installation of fast EV charging stations to be installed in residential facilities, fast and slow EV charging stations to be installed in commercial facilities, and fast EV charging stations to be installed in public parking lots. For fast EV charging stations located in residential facilities, the number of registered EVs and land value strongly influenced the amount of charging energy. Moreover, it was negatively correlated with population, indicating that fast EV charging stations should be installed in residential facilities in areas with a high ratio of EVs to population and relatively high income. For fast and slow EV charging stations at commercial facilities, the land value strongly influenced the amount of charging energy, suggesting that it is essential for commercial facilities to be installed in areas with high land values, i.e., relatively high-income areas. Fast EV charging stations at corporate facilities were found to contrast with residential areas, where the population and number of registered EVs are higher. For public parking lots, the number of registered EVs strongly influenced the amount of charging energy for slow EV charging stations.

Tourist areas in South Korea. In tourist areas, the methodology in this paper can be used to prioritize fast EV charging stations to be installed in public institutions and public parking lots. On the other hand, Jeju Island, which was used as a case study, has a unique feature: the proportion of rental cars is very high, so it is necessary to be cautious in generalizing.

Rural areas in South Korea. In rural areas, the methodology in this paper can be used to prioritize installing slow EV charging stations in residential facilities. On the other hand, it is challenging to optimize other facilities in the current situation because of the high distribution of socioeconomic factors. Therefore, EV installation sites in rural areas should be more segregated and analyzed for prioritization.

The correlation between the total score and the amount of charging energy was unclear in some facilities (correlation

TABLE 21. Optimized weights and correlation analysis for EV charging facilities according to the type and purpose – case of scenario-facility.

Type	Purpose of Facility	Population (weight)	Number. of EVs (weight)	Traffic Volume (weight)	Land Value (weight)	Total Score (correlation coefficient)
Fast	Residential	10.0000	−0.9823	10.0000	−0.1717	0.0434
	Commercial	−0.3962	−0.0485	0.9083	9.5365	0.3642
	Corporate	−0.2086	−0.6213	1.2130	9.6170	0.1892
	Public institution	5.6064	3.3090	2.1856	−1.1009	0.2739
	Public parking lots	1.6048	2.7942	1.1827	4.4191	0.3204
	Others	1.5991	0.6602	5.4629	2.2779	0.1387
Slow	Residential	10.0000	−0.9823	10.0000	−0.1717	0.0434
	Commercial	−0.3962	−0.0485	0.9083	9.5365	0.3642
	Corporate	−0.2086	−0.6213	1.2130	9.6170	0.1892
	Public institution	5.6064	3.3090	2.1856	−1.1009	0.2739
	Public parking lots	1.6048	2.7942	1.1827	4.4191	0.3204
	Others	1.5991	0.6602	5.4629	2.2779	0.1387

TABLE 22. Optimized weights and correlation analysis for EV charging facilities according to the type and purpose – case of scenario-type.

Type	Purpose of Facility	Population (weight)	Number. of EVs (weight)	Traffic Volume (weight)	Land Value (weight)	Total Score (correlation coefficient)
Fast	Residential	3.0851	1.5440	3.1220	2.2489	0.2544
	Commercial	3.0851	1.5440	3.1220	2.2489	0.2544
	Corporate	3.0851	1.5440	3.1220	2.2489	0.2544
	Public institution	3.0851	1.5440	3.1220	2.2489	0.2544
	Public parking lots	3.0851	1.5440	3.1220	2.2489	0.2544
	Others	3.0851	1.5440	3.1220	2.2489	0.2544
Slow	Residential	10.0000	−1.8183	4.3601	−2.5418	0.1468
	Commercial	10.0000	−1.8183	4.3601	−2.5418	0.1468
	Corporate	10.0000	−1.8183	4.3601	−2.5418	0.1468
	Public institution	10.0000	−1.8183	4.3601	−2.5418	0.1468
	Public parking lots	10.0000	−1.8183	4.3601	−2.5418	0.1468
	Others	10.0000	−1.8183	4.3601	−2.5418	0.1468

coefficient < 0.2). This may be due to key factors other than those used in this paper. Hence, more key factors need to be analyzed in future research. Possible key factors may include road congestion and population according to age group.

In this study, our methodology uses public data, which enhances its transferability to other countries or regions. While traffic volume and land value data may not be readily available everywhere, our methodology can be adapted by using proxy variables such as the number of road lanes and income levels as proxies for traffic volume and land value, respectively. Many countries provide open access to transportation infrastructure data and socioeconomic indicators, making it possible to apply our approach with minor modifications to suit the local context. By substituting these proxy variables, our methodology can be extended to evaluate suitable locations for EV charging station deployment in different geographic areas, taking into account regional differences in data availability.

VII. CONCLUSION

Many studies have analyzed the factors influencing the amount of charging energy at EV charging stations, but few have applied the results to the real world. This study analyzed the correlation between various factors and the amount of charging energy at EV charging stations in the Republic of Korea. The amount of charging energy at EV charging stations varies according to the type of EV charging station (fast and slow) and the purpose of the facility where the EV charging station is installed.

The methodology in this study was developed to help develop EV charging station deployment policies by suggesting which EV charging stations should be prioritized so that future EV charging stations can be prioritized in locations where more charging energy is expected. This is expected to make EV charging stations more cost-effective and improve charging convenience for EV users. This paper provided an example from the Republic of Korea. Nevertheless, given the number of EVs and vehicles in the Republic of Korea, this paper presented an example that could help countries in similar situations.

However, this study has several limitations. First, the analysis was conducted using only current data, so it does not reflect the trend of increasing EV penetration in the future; second, the influence of factors such as the advancement of EV charging technology was not considered; and third, there may be other socioeconomic factors that influence the amount of charging energy at EV charging stations.

Therefore, future studies need to develop EV charging station demand forecasting models that reflect the increasing trend of EVs assuming 5 and 10 years from now. They should also include variables such as new technology trends and identify and analyze more and different variables that influence the amount of charging energy to enable more sophisticated forecasts. This will enable forward-looking and efficient optimization of EV charging infrastructure and deployment plans.

APPENDIX

See Tables 20–22.

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