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A data-based scheduling methodology for constructing hydrogen refueling stations

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Abstract−Hydrogen is drawing increasing attention as a carbon-neutral energy carrier. The effects of climate change are increasing the pressure to establish a hydrogen energy infrastructure. To facilitate the transition to hydrogen energy, a large number of hydrogen refueling stations (HRS)s will need to be constructed throughout the entire transportation network. With a limited financial budget, constructing them simultaneously is not possible. However, it is economical to develop a systematic decision-making framework for determining construction priorities for HRSs. In this study, we propose p-median based mixed integer linear programming (MILP) models to establish location and construction priorities. The models aim to maximize the contribution impact that is represented by the sum of average distances between HRS and its allocated hydrogen vehicles. The metropolitan city of South Korea, Seoul, is used as a case study to illustrate the applicability of the proposed methodology.

Keywords: Hydrogen Refueling Station (HRS), P-median, Construction Scheduling, Optimization, Modeling

INTRODUCTION

Climate change has become a critical global issue, necessitating the development of alternative carbon-neutral energy systems to combat carbon-oriented global warming. Hydrogen, as an energy carrier, holds great promise in addressing this challenge. It offers a clean circulation structure, long-term storage capability, and efficient long-distance transportation, making it a key component of future energy systems [1]. Fuel cell electric vehicles (FCEVs) fueled by hydrogen have gained prominence as environmentally friendly transportation options. Unlike traditional petroleum vehicles, FCEVs do not emit carbon [2]. Compared to electric vehicles, they have a longer mileage and shorter refueling time. The only barrier for FCEVs is to establish efficient hydrogen supply chains involving hydrogen production, transportation, and storage at hydrogen refueling stations (HRS) [3].

HRSs serve as crucial facilities in the hydrogen supply chain, playing a frontline role in making FCEVs accessible to the public. However, there exists a challenge in striking a balance between the demand for FCEVs and the construction of sufficient HRSs. This dilemma is often referred to as the "chicken-and-egg" problem, where the sale of FCEVs relies on the availability of HRSs, but the construction of HRSs requires enough FCEVs [4]. Therefore, it is essential to ensure cost savings through economies of scale by strategically locating multiple HRSs where the demand is concentrated, thereby maximizing convenience for FCEV drivers [5]. At present, the introduction of HRSs is still in its early stages, resulting in a limited number of available facilities [6].

In terms of demand and supply, two main types of information should be considered when selecting the location of a HRS. The first is spatial and temporal information on the location of FCEVs, and the second is hydrogen production and delivery. As the hydrogen economy begins to take shape, the establishment of a comprehensive hydrogen supply chain encompassing production, storage, transportation, and refueling becomes crucial. The focus should be on constructing a substantial number of HRSs, which serve as a key element of the supply chain. The importance of HRS preparation has garnered significant attention in the literature.

Most existing activities are mainly based on individual regional cases, and a geographic information system (GIS)-based model was developed for locating HRSs in Sacramento, California, in terms of the average operating time [7]. A hydrogen refueling infrastructure was reviewed for the U.S. in the State of California with the goal of selling 1.5 million units of zero-emission vehicles by 2025 [8]. In terms of spatial and temporal issues, the energy and environment perspective were considered in Irvine, California to promote FCEVs, and the environmental impact of HRS placement was analyzed [9]. Based on the prediction that fossil fuel vehicles will be converted into FCEVs in Yokohama, Japan, the optimal number of HRSs that minimize the sum of operating costs from operation to HRSs was estimated [10]. The study conducted an analysis of the cost, emissions, and energy use of hydrogen production and transportation to HRSs based on the demand location [11]. As a result of calculating the economic feasibility and stability of hydrogen transport infrastructure using the hydrogen delivery scenario analysis model, the capacity of the HRS should be at least 1,000 kg/h, and if the capacity of the HRS is small, an on-site method is proposed [12]. As of the end of 2020, the country with the most FCEV sales in the world is South Korea, with about 10,000 registered units. Comparing the number of HRSs and FCEVs, Korea has 52 HRSs, with 194.1 units per HRS, and the United States, China, and Japan have 146.9, 99.3, and 30.7 units, respectively [13]. To make hydrogen-fueled FCEVs more economical and popular, it is essential to construct a sufficient number of HRSs that can compete with

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existing fossil fuel-based vehicle infrastructure [14,15].

As HRSs grow in scale and scope compared to that of a fossil fuel supply chain, a statistical model that was concerned with predicting the hydrogen demand in terms of the type, size, location, and time of the HRS was developed [16]. Estimating the present and future values of origin-destination demand is challenging, and previous attempts utilized mixed-integer linear modeling to estimate travel time [17]. The construction cost of an HRS depends on various factors, such as the capacity of the refueling station, the number of storage tanks and dispensers, and the method of supplying hydrogen. The construction costs were roughly estimated to range between 0.86 M$ and 11.8 M$ [5]. According to the hydrogen fuel cell partnership, the total construction cost of a hydrogen filling station varies from $2 million to $3.2 million depending on the supply method [18]. The construction cost of an HRS is very high, 10-15 times that of current operational fossil fuel gas stations [19]. Because of the high construction costs of an HRS, it is impossible to simultaneously build HRSs at all the locations needed to meet the hydrogen demand of FCEVs. Therefore, the most realistic way to maximize the impact of a HRS is to calculate the best locations necessary for FCEVs to use HRSs and build HRSs according to their priorities within the allowable budget limit.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of existing literature on location optimization algorithms for HRS selection. Section 3 presents an overview of the HRS priority selection problems and introduces Model 1 and Model 2, which are mathematical programming models based on the p-median approach. Section 4 presents numerical examples to illustrate the applicability and efficiency of our proposed models. In Section 5, we engage in a comprehensive discussion of the results, comparing our models with other approaches, addressing limitations, and suggesting future research directions. Finally, Section 6 concludes the paper by summarizing our key contributions and practical implications for advancing the hydrogen economy and promoting widespread adoption of FCEVs through strategic HRS planning.

LOCATION OPTIMIZATION ALGORITHM LITERATURE REVIEW

Multiple methodologies have been proposed to select the optimal locations of HRSs. In particular, mathematical studies can be categorized into two types, node- and path-based models, depending on the way they deal with demand [20]. In the node-based demand model, the demand is represented as a set of nodes. A set of demand points and a set of HRS locations are formulated using a distance matrix [21,22].

A p-median model [23] aims to find the locations that meet the sum of all demands from a selection of potential locations to multiple location candidates at the minimum cost [24]. Specifically, the total weighted distance between the hydrogen demanding point and p facility, denoted by an integer p is minimized in the model. The p-median model is expanded as a multi-objective programming model to deploy a finite number of existing gas stations [25].

A p-center model is concerned with minimizing the distance to the farthest demand and is a min-max problem because it minimizes the maximum distance [23]. The goal of the model is to minimize the total transportation costs between the facility and the destination. It is used to find the minimum number of facilities to cover all customers or to maximize the demand guaranteed by a specified number of facilities. P-center and p-median problems generally belong to NP-hard problems for which a polynomial algorithm is used to compute an exact solution, except for enumerating the number of cases [26]. As the number of nodes increases, the computation time increases exponentially.

The p-center and p-median problems are fundamental optimization problems used in location analysis. The p-center problem seeks to identify the optimal location for a single facility, minimizing the maximum distance between the facility and a point of demand. On the other hand, the P-median problem aims to find the optimal locations of multiple facilities, minimizing the sum of distances from each point of demand to the nearest facility. The covering model considers the range of maximum operation of stations, and a station that satisfies a demand node is evaluated based on the distance between stations [27]. The model can be further divided into two types: set covering and maximal covering [21]. The set covering model is concerned with reducing the number of stations required, and the maximal covering model maximizes the amount of demand allocated to the stations given the number of stations.

Path-based models were also studied. Demands are represented as flows along the origin-destination path and not from a node. It is assumed that the driver stops midway through the route to refuel. The concept of the maximum covering location model is used to search for a solution that meets the demand of the node set to the maximum. A flow-capturing location model (FCLM) is proposed to maximize traffic flow [28]. In the FCLM, it is assumed that the driver only refuels once during the route. For a case where the driver detours from the shortest route and visits the refueling facility, the deviation flow capturing location model, DFCLM is proposed [29]. Considering the characteristics of alternative fuel vehicles and the arrangement of several refueling stations along the route, a flow-refueling location model (FRLM) is proposed [30].

There are also studies reporting on the real-world construction of HRSs. A network of hydrogen refueling stations for highways in California was investigated using the p-median model [31]. A "fuel-travel-back" approach that considers the habits of drivers who want to reduce refueling time was also proposed [32]. Using vehicle mileage data in Southern California in the context of a mixed integer programming model, it was demonstrated that fuel accessibility could be achieved with only 18% of the existing number of gas stations.

There is a study compared the p-median and flow-refueling models to determine the optimal location of an alternative fueling station in Florida, U.S. [20]. The results of the study show a large difference between the two models at the state level and at the city level. As the value of p increased, the optimal location of the FRLM became more stable than that of the p-median.

An economic evaluation was performed by considering the life cycle costs, and a model for deploying hydrogen refueling stations on highway routes in China was presented using particle swarm optimization as a location optimization solver [33]. The potential demand and quantity of hydrogen were predicted using a regression model, and GIS analysis for 2020 and 2025 using p-median was used to predict the efficiency of the covered refueling stations at the city level [34]. For location selection of HRSs, p-median was conducted for Beijing, China, using a gas station network, geographic information system (GIS), and demographic and economic data [35]. For the efficient operation of HRSs, changes in fuel refueling time according to pressure conditions were presented. A more effective response of hydrogen demand and the incorporation of these results into future studies have yielded realistic results [36].

The HRS location problem was transformed into a bi-level problem model to determine whether to refuel according to the hydrogen refueling demand or the driver's deviation in the hydrogen network [37].

The feasibility of site planning was compared with the site selection plan for an HRS in California, and local optimization was avoided through a genetic algorithm that combined a greedy algorithm and an annealing algorithm. Through the decentralized hydrogen production plan, a case was presented for 2030 in the southeastern part of Seoul by efficiently establishing a hydrogen refueling infrastructure [38]. By dividing the road types into general roads, highways, and roads for buses, the set-covering model and p-median algorithm were sequentially applied to present a plan for HRSs across Korea from 2020 to 2040 [39]. For taxis in Paris, France, the p-median algorithm was modified to minimize the distance between HRSs and candidate sites, and a location algorithm that maximized the distance between HRSs was proposed [40].

For Yokohama, Japan, an HRS deployment plan was developed for 2020 to 2030, using a robust centralized planning model (RCPM). For demand forecasting, three scenarios were used to predict the number of FCEVs: optimistic, medium, and pessimistic. An analysis of the effect of the refueling demand share showed that as the refueling demand share increased, more refueling stations were added to the network to meet the refueling demand [41]. A multiobjective model was compared with cost, risk, and population coverage analyses as a single objective to construct 77 hydrogen refueling stations from 2020 to 2030 in Adana, Turkey. The minimum number and capacity of refueling stations minimize costs and risks and maximize the number of beneficiary populations [42].

Equalizing the workload of facilities is one of the problems considered in selecting facility locations. The problem of location selection was proposed as a function that minimizes the maximum demand allocated to electric vehicle charging stations. A mixed water purification planning model was proposed based on the load-leveling technique for the selection of the location of electric vehicle charging stations [43].

For our study, the focus is on determining the optimal location for HRSs. We assumed that the precise locations of each hydrogen vehicle were not available and that existing gas stations would be converted into hydrogen filling stations as needed. Hence, it was essential to consider the average convenience of users when deciding the future hydrogen station locations. Considering these aspects, the P-median problem was found to be more suitable than the P-center problem for our specific case, and thus, the P-median problem was chosen as the basic algorithm to address this location optimization challenge. From review of previous studies, it is concluded that most studies were only concerned with selecting the locations of HRSs. Few studies have explicitly addressed computing the construction priority of HRSs. This study aims to bridge this gap. Mathematical models were proposed to determine the priority of an HRS based on computing the maximum daily hydrogen supply. Specifically, the HRS allocation model for HRSs was created based on the p-median model, and a node-based model that minimizes the sum of distances between demanding sites and candidate sites for HRSs is proposed.

The remainder of paper is organized as follows. The HRS priority selection problems are outlined. P-median based mathematical programming models are then presented. Numerical examples are presented to illustrate the applicability of the models with some comments.

PROBLEM OVERVIEW

HRSs remain the biggest obstacle to the large-scale development of hydrogen supply chains due to the higher construction and operating costs compared with electric vehicles and gas stations. Therefore, their locations should be selected more strategically within a limited financial budget. Furthermore, this study highlights that the construction schedule of the selected HRSs should be determined to generate the maximum impact.

This study is concerned with constructing a large number of HRSs to meet the hydrogen demand of FCEVs. Because FCEVs are geographically dispersed, HRSs should be constructed over multiple regions. A hydrogen supply chain should be constructed based on the production, delivery, and storage of hydrogen on a large scale. The hydrogen supply chain should be optimized by selecting the best location for the HRSs to meet the FCEV demand in a cost-efficient manner. A decision-making framework should be prepared to compute the optimal construction priorities for the selected HRSs. To achieve this goal, a two-step approach is proposed in this study. First, the optimal position of the HRSs is selected, and the costs to determine the construction priorities of the stations are then evaluated.

In the model, the objective function is to minimize the sum of the distances between the hydrogen demand and HRS. Currently, the maximum hydrogen storage capacity per day in a HRS is fixed at approximately 250 kg [42]. As a constraint, the maximum capacity of hydrogen that an HRS can handle per day is 250 kg, and the sum of the hydrogen demand in the allocated candidate sites cannot exceed this amount. All candidate sites must be allocated to HRSs without exceptions. The number of new HRSs is then P_{HRS}. The decision variables are binary variable restrictions.

Fig. 1 shows an example of the overview of a hydrogen supply chain and our focus in this study.

HRS site selection and problem prioritization were transformed into a node-based p-median model. In the model, the capacity of all HRSs was assumed to be the same. Because of the early development stage of HRSs, this was judged as a realistic assumption that the same model was supplied to the HRS rather than only diversifying the capacity of the HRS. This paper does not include HRS for commercial vehicles, such as buses, due to different capacities and filling pressures.

The HRS is critical to a hydrogen supply chain and is an essen-

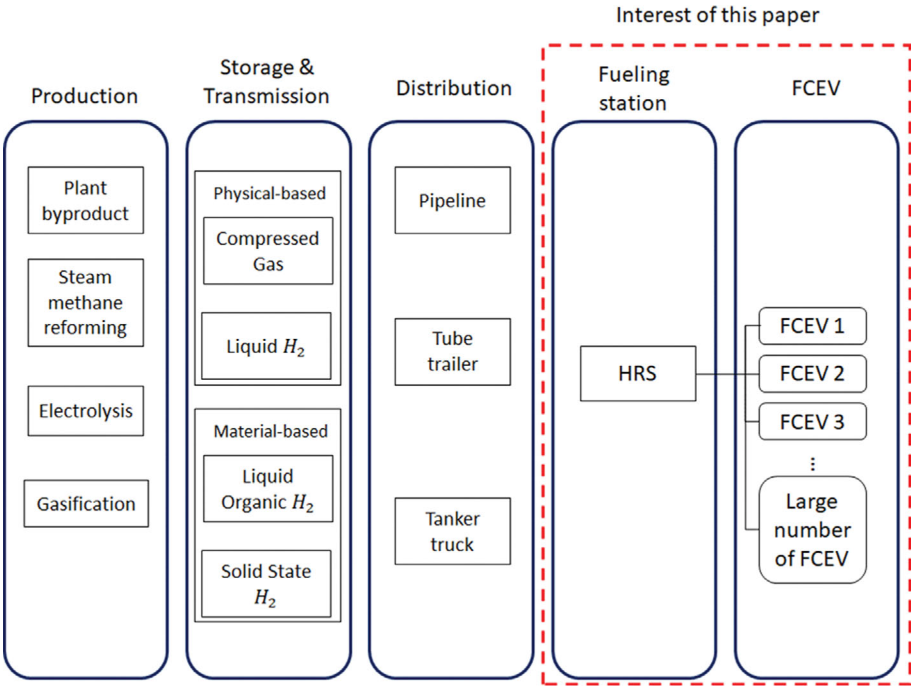


Fig. 1. Overview of Hydrogen Supply Chain and focus of this study.

tial element for hydrogen vehicle owners and has the character of a commercial facility and a public good. Hydrogen vehicles cannot be used without HRSs, and hydrogen production is an important process for final consumers.

The HRS proposes a location selection model that considers hydrogen load balancing and reduces the average mileage of drivers to alleviate the imbalance caused by the concentration of demand to specific HRSs and reflect the equity and efficiency of public services.

1. Model 1

Model 1 is a mathematical model that minimizes the sum of the FCEVs position and distance between HRSs to select the location of hydrogen HRSs and find a suitable candidate site that does not exceed the daily hydrogen supply capacity. The nomenclature at the end of paper summarizes the sets, variables, and parameters used in the model.

Decision Variables

x_{ij}	1 If FCEVs at node *i* is assigned at HRS node *j*, 0 otherwise
y_j	1 If HRS is built on node *j*, 0 otherwise

Objective

$$\text{Minimize} \sum_i \sum_j d_{ij} x_{ij} \tag{1}$$

Subject to

$$\sum_i x_{ij} F_i \leq C_{max} y_j \qquad \forall j \tag{2}$$

$$\sum_j x_{ij} = 1 \qquad \forall i \tag{3}$$

$$\sum_j y_j = P_{HRS} \tag{4}$$

$$x_{ij} - y_j \leq 0 \qquad \forall i, j \tag{5}$$

$$y_j \in \{0, 1\} \qquad \forall j \tag{6}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \tag{7}$$

The objective function (1) minimizes the distance between the FCEV and HRS. Constraint (2) ensures that the sum of the hydrogen demand of candidate sites allocated to the HRS does not exceed C_{max}. Constraint (3) ensures that all FCEVs are allocated to HRSs. Constraint (4) guarantees that the number of new HRSs is P_{HRS}. Constraint (5) ensures that all candidate sites are only allocated to candidate sites where HRSs are installed. Constraints (6) and (7) are for binary variables.

Model 1 has a function that minimizes the sum of the distance between an FCEV and candidate HRS location. Its results show a trend of decreasing average mileage. However, some HRSs have a result in which hydrogen demand is concentrated close to the limit capacity of HRSs. This leads to an overload of HRS facilities and prolonged waiting time for users refueling with hydrogen. As a solution, a new model is proposed that introduces load balancing, which lowers the maximum refueling demand allocated to each station. Load balancing is added to the objective function and constraints to minimize the hydrogen demand allocated to each HRS. As the demand for hydrogen allocated to HRSs changes, the constraints are added to prevent the selected HRSs from refueling into Model 1.

2. Model 2

Model 2 minimizes the maximum value of the hydrogen amount allocated to each HRS by changing the objective function and the constraints in Model 1 to balancing the amount of hydrogen allocated to each HRS. Constraints are added to use the HRS locations selected in Model 1. To maximize the effect of load balancing used in Model 2, the weight W is applied to the objective function.

Decision Variables

L_{max} Maximum daily hydrogen refueling allocated to an HRS

Objective

$$\text{Minimize } \sum_i \sum_j d_{ij} x_{ij} + W L_{max} \tag{8}$$

Subject to

Constraints (2)-(7)

$$\sum_i x_{ij} F_i \le L_{max} \quad \forall j \tag{9}$$

$$y_j = 1 \quad j = 1, 2, \ldots, P_{HRS} \tag{10}$$

The objective function (8) minimizes the sum of the distance between the hydrogen car, HRS, and the weighted L_{max} value. Con-

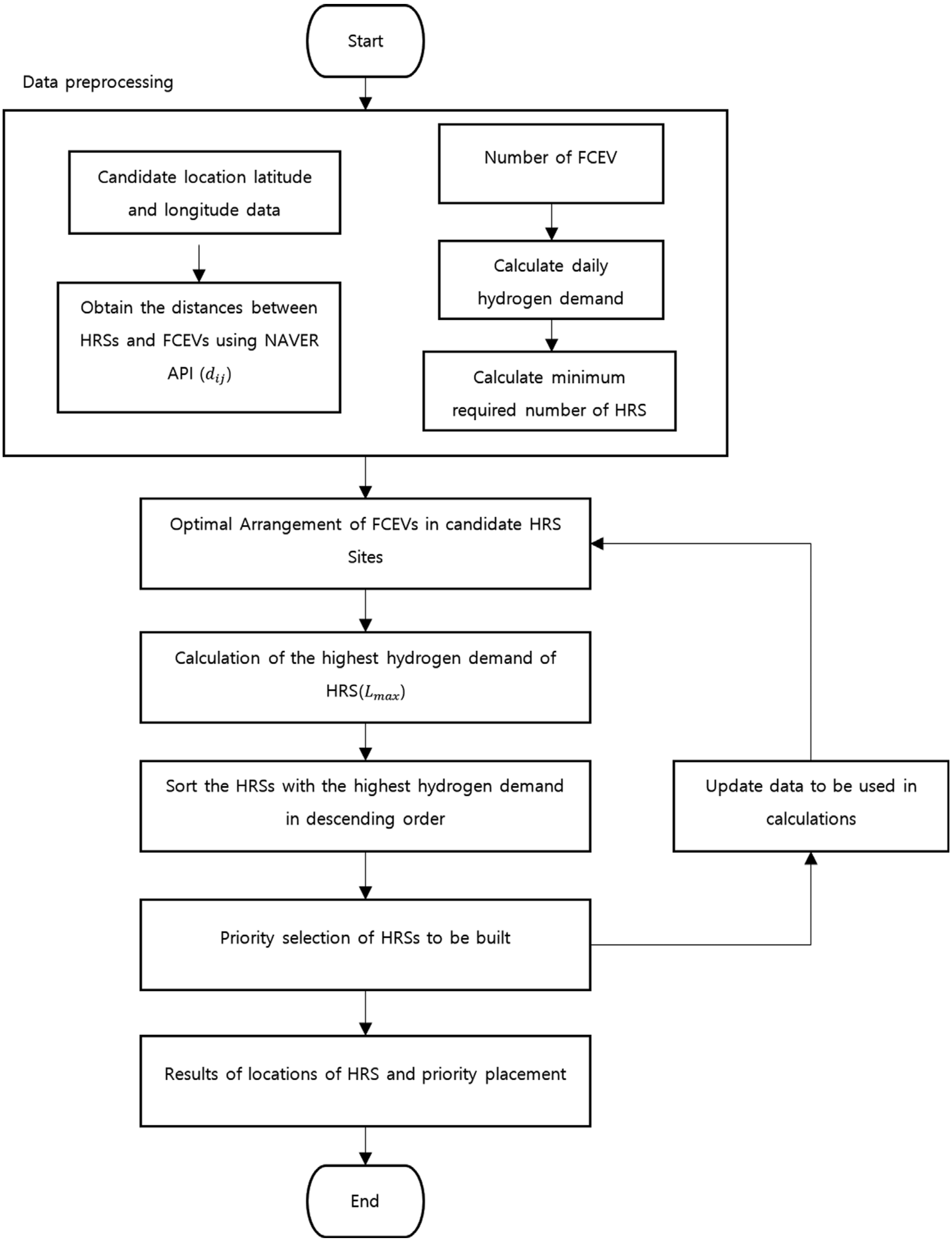


Fig. 2. Flowchart for the selection of HRS locations and priorities.

straint (9) ensures that L_{max} is the maximum value of the daily hydrogen demand allocated to the HRS. Constraint (10) allows the HRS candidate site selected in Model 1 to be calculated as the same HRS when calculated in Model 2.

3. Selecting Construction Priority of HRS

Fig 2 shows the overall decision making flow chart in deciding the location and priority of HRSs. Based on Model 1 and Model 2, the priority construction order of the HRSs is determined by considering the amount of hydrogen allocated to each station from the selected candidate sites. Each candidate site is evaluated based on the amount of hydrogen required, which is determined by the number of hydrogen vehicles registered in the area and their respective fuel efficiency. It is reasoned that HRSs with higher hydrogen demand should be given higher priority in the construction order. Therefore, the proposed approach suggests building HRSs in descending order, starting from those with the highest amount of hydrogen required.

NUMERICAL EXAMPLES

1. Demand Estimation

A hydrogen supply chain for Seoul, South Korea, was designed in this study. The main assumptions in constructing the supply chain are worth mentioning. It was assumed that a sufficient number of FCEVs had been purchased and were operational in the area. The necessary number of HRSs was then constructed at the appropriate location to meet the demand of the FCEVs.

Seoul, the capital of Korea, was the target location for the application of the proposed model. As of August 2021, the number of FCEVs registered in Seoul was 2,109, and the number of FCEVs required per day was calculated and applied to the model. As shown in Table 1, the fuel demand (F) allocated to each candidate site was calculated by multiplying the number of FCEVs by the average daily travel distance of 40 km and dividing the fuel efficiency of Hyundai Nexo vehicles, supplied in Korea, by 96 km/kg.

The HRS facilities in South Korea have a daily refueling capacity of 250 kg, as of 2021. In an ideal case, up to 70 vehicles can be refueled per one day based on 14 hours of operation. Assuming an ideal situation, the maximum daily capacity of each HRS was thus assumed to be 250 kg/day (C_{max}).

The FCEVs are registered in the administrative district in which they belong. Using this as a case study, Case 1 assumes that the location of 25 district offices, an administrative district under the Seoul Metropolitan Government, was a candidate site for an HRS. Case 2 assumes 545 locations, which were the locations of gas stations in Seoul. Case 1 divided 878.75 kg, the calculated amount of hydrogen listed in Table 1, according to the location registered at 25 locations, and Case 2 also divided 545 locations to create an input file.

Case 2 examines a scenario where the number of hydrogen vehicles increases in the future. To estimate the trend of hydrogen vehicle growth, a quadratic equation was fitted to the data of hydrogen vehicle registrations in Seoul from 2018 to August 2021. The fitting equation obtained was $y=64.75x^2+491.75x-515.25$, where x represents the number of years from 2018.

Assuming a time frame of approximately 7 years into the future from the base year of 2021, it is estimated that there will be 5,417 hydrogen vehicles registered. This is approximately 2.6 times the number of hydrogen vehicles registered in 2021 (2,109 vehicles). This estimation serves as a basis for evaluating the future demand for hydrogen filling stations and determining the priority order for their construction.

This case considers an off-site HRS type that can supply 250 kg of hydrogen per day. While on-site HRSs offer independence from the hydrogen supply network, their higher initial construction costs make off-site HRSs a more suitable choice for this study. Within the off-site methods, a tube-trailer approach was chosen over a pipeline system. The tube-trailer method provides greater flexibility in establishing the initial hydrogen refueling network and also offers a slightly lower initial cost.

1. All HRS models were of one the same type, and the daily refueling capacity was limited to 250 kg/day.
2. The location of a gas station registered in Seoul as of August 2021 was considered a candidate site for the construction of an HRS.
3. This paper focuses on off-site HRSs, which receive their hydrogen supply from external sources.

In this study, IBM CPLEX Optimizer 20.1.0.0 was calculated on Python Anaconda Jupiter laptops as an integral linear programming solver. The calculation was performed on a computer with i9-9900 KS@ 4.00 GHz and 64 GB memory specifications.

2. Estimation of Optimal Number of HRS

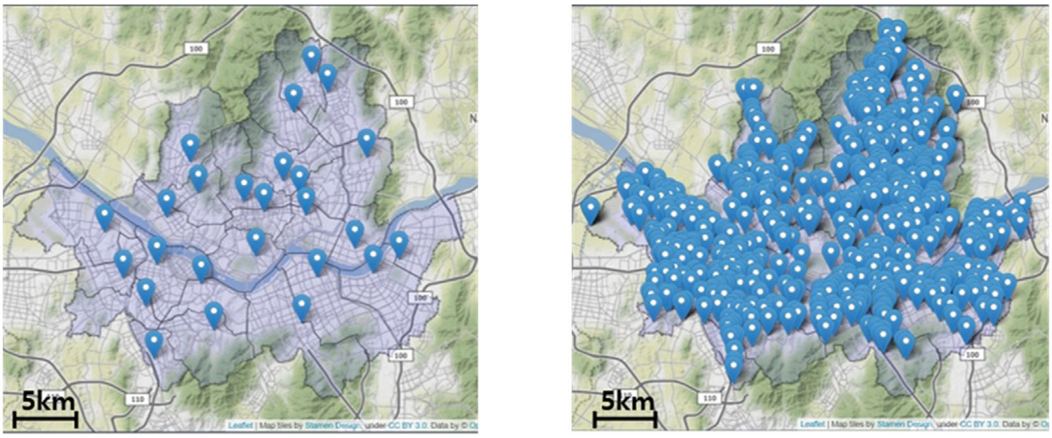
The minimum number of HRSs required in the region was predicted based on the number of existing hydrogen vehicles. The amount of hydrogen required for refueling demand was calculated by multiplying the number of hydrogen vehicles by the average daily distance traveled and dividing the fuel efficiency of the NEXO vehicle, an FCEV vehicle in Korea. The total number of HRSs was calculated by dividing the total amount of hydrogen required by the supply capacity of each HRS per day.

$$P_{HRS}=\frac{\Sigma_{i=1}^{n}F_i}{C_{max}} \tag{11}$$

Eq. (11) was applied to the hydrogen demand allocated to each

Table 1. Basic information on hydrogen in South Korea, as of August 2021. The number of registered FCEVs, average mileage of Seoul drivers, and daily hydrogen demand calculated through the combined fuel efficiency of the Nexo vehicle are shown

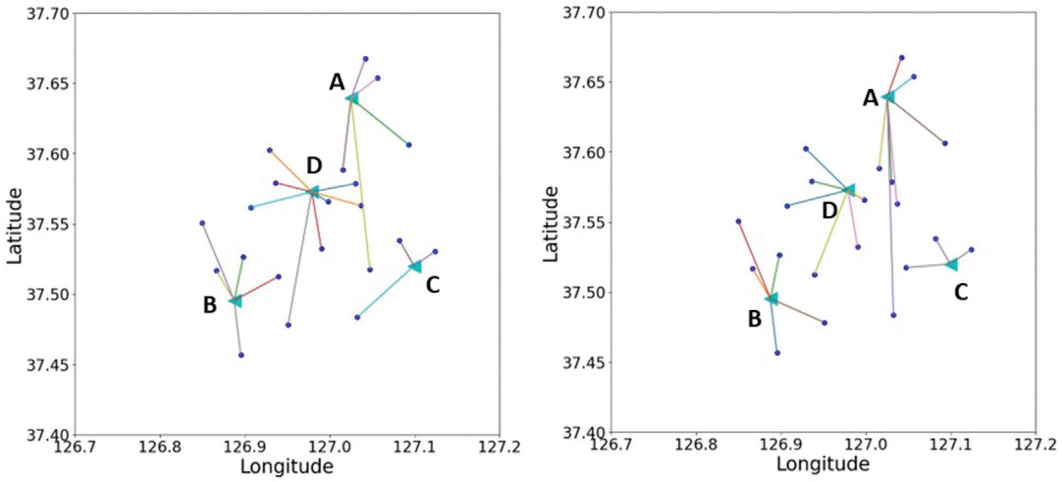
	Number of registered FCEV in Seoul	Average driving distance per day	Fuel efficiency	Amount of hydrogen required per day	Minimum number of HRS (P_{HRS})
Unit	#	km	km/kg	kg H_2	
2021	2,109	40	96	878.75	4
2028	5,417			2,257.01	10



(a) Case 1: Construction candidates at 25 district offices in Seoul, South Korea

(b) Case 2: Candidate sites at 546 gas stations in Seoul, South Korea

Fig. 3. A Graphical Representation of the locations of HRS candidates in (a) Case 1 (25 candidate HRS locations) and (b) Case 2 (545 station candidate locations).



(a) Result of applying Model 1 to Case 1

(b) Calculated results from Model 2 with load balancing applied to Case 1

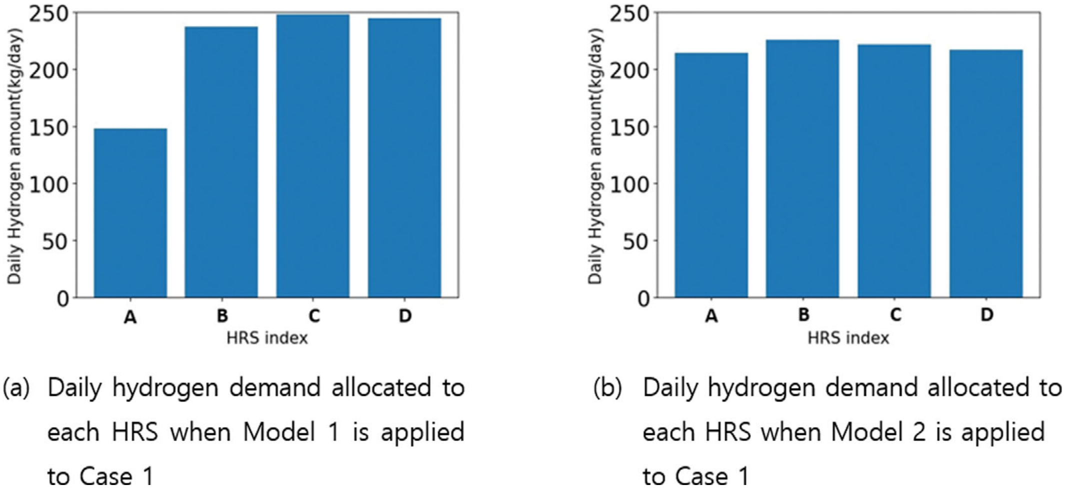
Fig. 4. Results of Case 1 with 25 candidate HRSs according to Models 1 and 2.

candidate site to calculate the minimum number of HRSs required. Case 1 had 25 candidate sites and the hydrogen demand was 878.75 kg. Case 2 had 545 candidate sites and the hydrogen demand was 2,197 kg, which was 2.5 times that of Case 1. The number of HRSs required was 4 for Case 1 and 10 for Case 2.

As of August 2021, the 2,109 registered FCEVs in Seoul required 878.75 kg of hydrogen per day. Models 1 and 2 were applied under the assumption that four HRSs were needed in the first 25 candidate groups as Case 1.

To select the location of the HRS based on the distance between each candidate site, a distance matrix was prepared. To prepare this, the gas station location converted each address received through the oil price information site into latitude and longitude coordinates using NAVER Cloud Platform Geocoding APIs. Considering the boundary of the Seoul Metropolitan Government, the range of latitude and longitude was 37.40°-37.70°N and 126.7°-127.2°E, respectively. Fig 3 shows candidate sites for HRSs in Case1 and Case2 on the map. The distance between each HRS candidate location was calculated using the NAVER Directions 5 API using the converted longitude and latitude. To accurately represent the mileage between candidate locations in the complex road network of Seoul, the NAVER API was employed. Real-time mileage data was obtained by requesting the API with each candidate location as both the starting point and destination. Although the API provides additional details such as required time, stopover points, and toll information, for the sake of simplicity and focusing on the priority construction order of HRSs, only the mileage data was used in this paper.

Fig. 4 shows the results of the HRS allocation for FCEVs in each administrative district when Model 1 and Model 2 were applied to Case 1. Selected HRSs were marked with letters instead of the



(a) Daily hydrogen demand allocated to each HRS when Model 1 is applied to Case 1

(b) Daily hydrogen demand allocated to each HRS when Model 2 is applied to Case 1

Fig. 5. Differences in daily hydrogen demand allocated to selected HRSs in Model 1 and 2 in Case 1.

Table 2. The number of FCEVs and the number of candidate sites allocated to each model in Case 1. The daily hydrogen demand, average mileage between the candidate sites allocated to each station, and construction priority of the HRS are shown

Model 1					
HRS	Number of candidates allocated	Number of FCEV	Daily hydrogen demand (kg)	Average mileage (km)	Construction priority
A	6	355	147.9	27.96	4
B	6	570	237.5	8.98	3
C	4	596	248.3	30.18	1
D	9	588	245.0	6.68	2
Model 2					
HRS	Number of candidates allocated	Number of FCEV	Daily hydrogen demand (kg)	Average mileage (km)	Construction priority
A	8	514	214.2	27.64	4
B	6	542	225.8	9.32	1
C	4	532	221.7	30.19	2
D	7	521	217.1	7.04	3

node index number used during the calculation. In Fig. 4, the blue dots denote the FCEV drivers, and the triangles denote the HRSs. As the position of the allocated FCEVs changed, the average driving distances were (a) 18.45 km and (b) 18.55 km.

Fig. 5 and Fig. 7 (a) shows that the amount of hydrogen refueling concentrated in some HRSs was close to the average, as the standard deviation for each refueling station was reduced in (b). As a result of Model 2, to which load balancing was applied, (b), it was determined that the HRSs allocated with more refueling amounts than other HRSs, had a higher priority than other stations, and thus a schedule for preferential construction was made. The high amount of hydrogen refueling can benefit more hydrogen vehicle drivers.

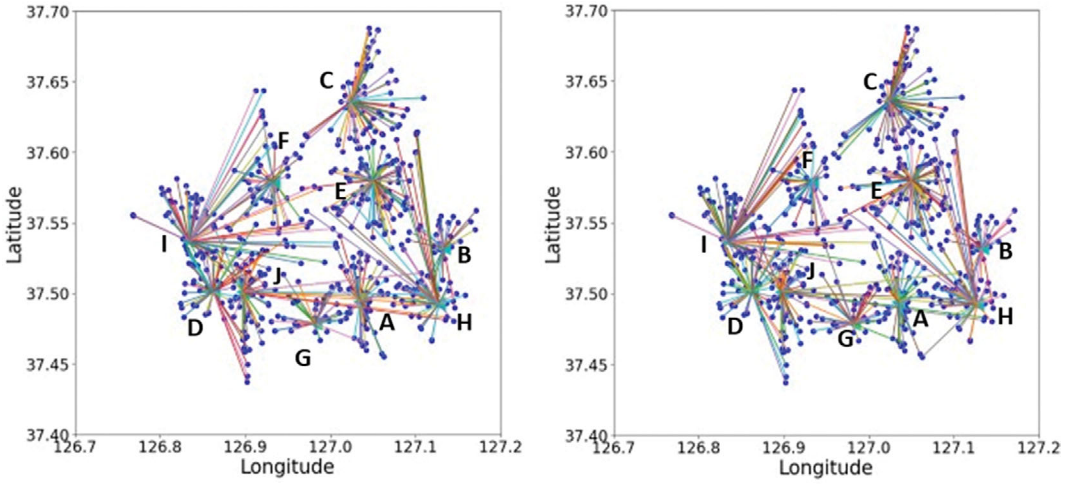
Table 2 lists the daily hydrogen demand according to the number of hydrogen vehicles, the average driving distance between the candidate sites, and HRSs allocated to each station as a result of Model 1 and Model 2. The higher the allocated amount of hydrogen demand, the higher the construction priority. As the demand for hydrogen allocated to HRSs changed in Models 1 and 2, the order of HRSs to be constructed first also changed.

When the daily hydrogen demand was 878.8 kg, four stations were needed. Table 2 shows that as a result of solving Case 1 to Model 2, in which load balancing was applied, the amount of hydrogen demand was evenly distributed. If the priority construction order of HRSs is proposed in the order of descending hydrogen demand, then the side with the largest number of hydrogen vehicles will benefit in the order of B-C-D-A. If four HRSs are built at 25 candidates in Case 1, the average driving distance will be that Model 1 is 18.45 km and Model 2 is 18.55 km.

Table 3 lists the construction priority of the HRS proposed by the models, and the maximum, minimum, median, and standard deviation of hydrogen allocated in the HRS. When comparing Model 2 based on Model 1, the maximum hydrogen value decreased from 248.33 kg to 225.83 kg, decreasing by 90.94%. On the contrary, the minimum value was 147.92 kg, which increased by 144.79% to 214.17 kg. The median value showed no significant difference from 241.25 to 219.38. The largest change in the standard devia-

Table 3. Priority for HRS construction, and the maximum, minimum, median, and standard deviation of hydrogen demand allocated to stations by each model

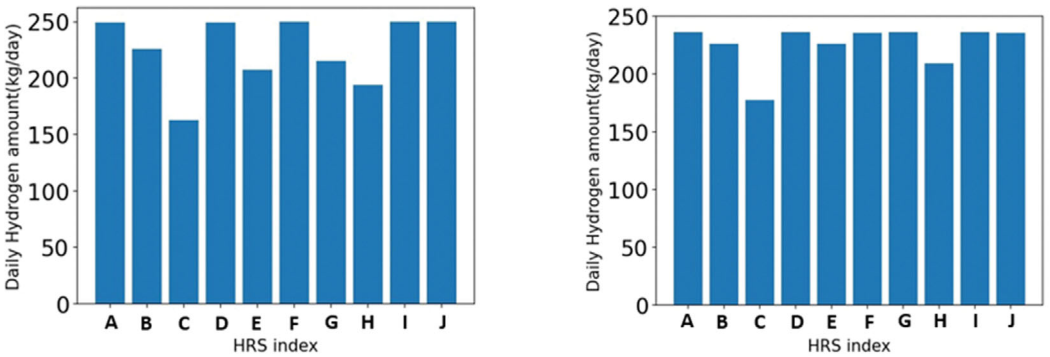
	Model 1	Model 2	Compared to the Model 1 and 2
Placement priority	C-D-B-A	B-C-D-A	
Maximum value of daily hydrogen demand of HRS (kg)	248.33	225.83	90.94%
Minimum value of daily hydrogen demand of HRS (kg)	147.92	214.17	144.79%
Median value of daily hydrogen demand of HRS (kg)	241.25	219.38	90.93%
Hydrogen demands standard deviation of HRS	48.06	5.13	10.67%



(a) Graphical representation of Case 2 result according to Model 1

(b) Graphical representation of Case 2 result according to Model 2 with load balancing

Fig. 6. Results of Models 1 and 2 that allocated 545 candidate sites for HRSs in Case 2.



(a) Daily hydrogen demand allocation according to Model 1

(b) Daily hydrogen demand allocation according to Model 2

Fig. 7. Daily hydrogen demand allocation to HRS in Case 2 according to Model 1 and 2.

tion was shown, and the value from 48.06 in Model 1 decreased to 5.13, which was 10.67%.

In contrast to the district office locations as candidates for HRSs in Case 1, Case 2 proposed 545 gas stations in Seoul as candidates for HRSs. It was proposed as candidate sites based on the assumption that if existing fossil fuel infrastructure is used as hydrogen refueling infrastructure, then it could accelerate the revitalization of the hydrogen economy. Based on the quadratic fitting equation, it is estimated that in approximately 7 years the number of hydrogen vehicles in Seoul will reach about 5,417 units, 2.6 times

Table 4. The number of FCEVs and the number of candidate sites allocated to each model in Case 2. The daily hydrogen demand, average mileage between the candidate sites allocated to each station, and construction priority of the HRS are shown

Model 1					
HRS	Number of candidates allocated	Number of FCEV	Daily hydrogen demand (kg)	Average mileage (km)	Construction priority
A	50	597	248.62	4.94	5
B	31	541	225.58	3.80	6
C	75	390	162.68	4.81	10
D	60	598	249.12	7.92	4
E	79	497	206.96	4.70	8
F	40	599	249.81	4.17	2
G	37	516	215.19	8.50	7
H	48	465	193.70	15.60	9
I	71	600	249.86	6.75	1
J	54	598	249.39	3.75	3
Model 2					
HRS	Number of candidates allocated	Number of FCEV	Daily hydrogen demand (kg)	Average mileage (km)	Construction priority
A	48	567	236.08	4.98	1
B	31	541	225.58	3.80	7
C	77	425	176.95	5.02	10
D	60	565	235.57	7.66	4
E	82	541	225.43	4.82	8
F	35	565	235.53	3.80	5
G	40	566	235.82	8.83	2
H	51	502	208.99	15.83	9
I	70	566	235.69	6.54	3
J	51	565	235.27	3.74	6

Table 5. Comparison of priority for HRS construction, and the maximum, minimum, median, and standard deviation of hydrogen demand allocated to stations by model in Case 2

	Model 1	Model 2	Compared to the Model 1 and 2
Placement priority	I-F-J-D-A-B-G-E-H-C	A-G-I-D-F-J-B-E-H-C	
Maximum value of daily hydrogen demand of HRS (kg)	249.86	236.08	90.94%
Minimum value of daily hydrogen demand of HRS (kg)	162.68	176.95	144.79%
Median value of daily hydrogen demand of HRS (kg)	237.10	235.40	90.93%
Hydrogen demands standard deviation of HRS	30.285	18.998	10.67%

higher than the current count. Consequently, to meet this increased demand, 10 additional HRSs will be needed to ensure an adequate hydrogen supply for the growing fleet of hydrogen vehicles.

Fig 6 shows the results of allocating FCEVs in each candidate site to ten HRSs according to Model 1 and Model 2 for Case 2. In Case 2, the daily demand for hydrogen is 2,257.01 kg, and 10 hydrogen filling stations are required. Table 4 indicates the detailed results of Model 1 and Model 2 in Case 2. The average mileage also tended to slightly increase to 6.49 km for Model 1 and 6.50 km for Model 2. For Case 1, Model 2 was less than 1; however, Case 2 had an increase in the number of candidate sites, and it was determined that the average driving distance in Model 1, which considers only the distance value, is smaller as the amount of hydrogen is considered. Based on the amount of hydrogen demand allocated to each station, the proposed construction sequence is I-F-J-D-A-B-G-E-H-C for Model 1 and A-G-I-D-F-JB-E-H-C for Model 2.

Table 5 shows the change in the amount of hydrogen allocated to each HRS when Models 1 and 2 are applied to Case 2. In the case of Model 1, the maximum value was 249.86 kg, the minimum value was 162.68 kg, and the standard deviation was 30.285. Model 2 had a maximum value of 236.08 kg, a minimum value of 176.95 kg, and a standard deviation of 18.998, indicating a decreasing trend. Like Case 1, it was decided that an HRS would be built in the order of the high demand for hydrogen in Model 2, to which

(a) Case 1: Construction candidates at 25 district offices in Seoul, South Korea

(b) Case 2: Candidate sites at 546 gas stations in Seoul, South Korea

Fig. 8. A Geographical result of the locations of HRS in (a) Case 1 (25 candidate HRS locations) and (b) Case 2 (545 station candidate locations).

load balancing was applied, and the HRS would be built first.

Fig. 8 shows the locations on the map when 4 and 10 HRSs were deployed in Seoul as a result of Cases 1 and 2. The model set the number of facilities (P_{HRS}) of the HRS so that the owner of the hydrogen vehicle can reach the location of the HRS within the minimum distance.

CONCLUSIONS

In this study, we addressed the crucial role of hydrogen refueling stations (HRSs) in the hydrogen supply chain, serving as facilities that compress and store hydrogen from various sources and distribute it to hydrogen vehicles and consumers. Maximizing driver convenience by minimizing average mileage was identified as a key factor for successful HRS utilization. However, concentrating HRSs in specific locations could lead to facility overload and increased waiting times for users. To counteract this, load balancing techniques were introduced at a time to minimize mileage and evenly distribute hydrogen refueling demand across HRSs.

To determine optimal HRS locations, we considered the district offices, which act as 25 administrative centers in Seoul, South Korea, and the existing 545 gas stations as candidate sites. Our aim was to gradually transform fossil fuel supply points into HRSs, contributing to the growth of the hydrogen economy.

As the number of candidate sites and factors to be considered increased, computational complexity also rose. Furthermore, increasing average mileage and hydrogen allocation to each HRS resulted in longer convergence times. To address these challenges, future studies will explore alternative calculation methods for improved efficiency.

Selecting appropriate HRS locations and prioritizing their construction are essential for revitalizing the hydrogen economy and enhancing user convenience. Further research will be conducted to facilitate the full-scale integration of HRSs, ensuring their widespread adoption and seamless integration into the transportation infrastructure.

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NOMENCLATURE

Indices

i : index of FCEV nodes
j : index of HRS nodes

Parameters

F_i : daily hydrogen demand for FCEV *i* [kg H_2]
d_{ij} : distance matrix between FCEVs *i* and HRS *j* [km]
P_{HRS} : number of HRSs
C_{max} : maximum capacity of supplying hydrogen per day [kg H_2]
N : number of FCEV sites
W : weight of load balancing factor

Abbreviation

FCEV : fuel cell electric vehicle
HRS : hydrogen refueling station
OD : origin-destination
DFCLM : deviation flow capturing location model
FCLM : flow-capturing location model
FRLM : flow-refueling location model
PSO : particle swarm optimization
GIS : geographic information system

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