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Hydrogen Supply Chain Network Optimization for Supporting Urban Hydrogen Vehicle Infrastructure Development

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ABSTRACT

This study addressed the rising concerns regarding greenhouse gas emissions and the depletion of fossil fuel resources by exploring hydrogen as a clean energy alternative. The Indonesian government established a national roadmap that prioritized the transportation sector as a starting point for hydrogen deployment. The objective of this research was to design and optimize a hydrogen supply chain network in Jakarta, a densely populated urban area considered strategic for early adoption. The study applied a two-stage approach. First, potential locations for Hydrogen Refueling Stations (HRS) were pre-selected based on spatial and demographic scoring using a modified gravity model. Then the second, the optimal placement of HRS and hydrogen suppliers was determined through a Mixed-Integer Linear Programming (MILP) method. The entire modeling and optimization process was implemented in Python, with MILP solved using the Gurobi optimizer. A total of 216 existing gas stations were assessed and grouped into five priority levels. The optimization was conducted for three planning periods: 2026-2030, 2031-2035, and 2036-2040. The results showed that integrating new HRS into existing infrastructure reduced land use and investment costs. Sensitivity analysis indicated that daily HRS capacity, hydrogen demand, and capital cost were the most influential factors. The study concluded that this integrated approach provides an efficient, flexible, and sustainable foundation for future hydrogen infrastructure development in urban regions.

Keywords: Gravity Model; Hydrogen Refueling Station; Hydrogen Supply Chain; Mixed-Integer Linear Programming, Urban Energy Transition

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1. INTRODUCTION

One of the most pressing global challenges today is the worsening environmental degradation driven by the uncontrolled emission of greenhouse gases (GHG), which accelerates global warming and climate change [1]. The transportation sector, heavily dependent on fossil fuels, remains one of the major contributors to these emissions[2]. In response, the global transition toward low-carbon energy systems has gained significant momentum, with hydrogen emerging as a promising clean energy alternative [3]. Urban areas, characterized by dense populations and concentrated energy demand, are considered ideal starting points for the introduction of hydrogen-powered vehicles [4].

Indonesia, as a rapidly growing economy with a strong decarbonization agenda, has articulated its commitment through the launch of a national hydrogen roadmap extending to 2060, with transportation identified as a priority sector [5]. This sector alone accounts for a significant share of the country's total GHG emissions [6]. The adoption of hydrogen fuel cell vehicles (HFCVs) offers substantial potential to reduce these emissions, especially in densely populated metropolitan areas [7] [8]. Nevertheless, the successful implementation of hydrogen mobility solutions hinges on the accessibility and optimal distribution of Hydrogen Refueling Stations (HRS), which serve as the final infrastructure link in the hydrogen supply chain[2], [9], [10].

Jakarta, the capital city of Indonesia, presents both strategic opportunities and logistical challenges for the deployment of HRS. On the positive side, the city's extensive road network and the existing network of gas stations offer a viable foundation for integrated HRS implementation [11]. However, issues such as limited land availability and the high capital expenditure required for new HRS installations pose significant barriers [12]. These constraints highlight the need for a more systematic and optimized approach to HRS network planning. In response to this challenge, this study introduces a hybrid framework that combines a gravity-based scoring model and clustering techniques for initial location screening, followed by a Mixed-Integer Linear Programming (MILP) model to optimize hydrogen supply chain network (HSCN) configuration. This integrative methodology takes into account land-use constraints, local demand characteristics, and Jakarta's urban structure while aligning with Indonesia's national hydrogen deployment goals.

Previous research has affirmed the effectiveness of MILP in optimizing facility location decisions within energy-related supply chains [13], [14]. Similarly, gravity models have proven useful in evaluating spatial interactions and identifying viable facility sites [15]. Notably, study by Crönert & Minner (2021) highlight the importance of strategic location selection and technology integration [16]. Gündüz et al. (2024) conducted research to determine the optimal HRS locations in specific urban areas, such as Istanbul [17]. Zhao et al. (2022) and Wu et al. (2024) focused on the development and deployment of HRS in cities across China, demonstrating approaches relevant to large-scale urban areas [18], [19]. Additionally, studies have been conducted to design sustainable and reliable hydrogen supply chain networks under mixed uncertainties for cities in Iran [20]. In South Asia, the design and optimization of hydrogen supply chains have been explored, particularly in Korea [21] and China [22]. However, most of these studies have focused on developed countries, often assuming greenfield development scenarios. They frequently overlook the potential of repurposing existing gas station infrastructure for hydrogen deployment, which is especially relevant in dense urban environments with limited land availability. Zhang (2024) highlighted the potential benefits of integrating HRS with existing gas station infrastructure as part of a low-carbon planning strategy, emphasizing its applicability to urban areas facing land-use constraints [12].

This study builds on global case studies and emphasizes the need for innovative approaches to hydrogen supply chain optimization in urban contexts like Jakarta, where space is limited and the integration of HRS into existing gas station infrastructure presents both challenges and opportunities. This study distinguishes itself by addressing Jakarta's unique urban context and proposing the integration of HRS into existing gas station infrastructure, thereby mitigating land-use constraints and investment costs. In addition, the model incorporates phased demand projections based on the *Indonesia Hydrogen Roadmap*, a dimension largely absent in earlier literature. By combining gravity-based scoring and MILP within a policy-aligned framework, the proposed model offers a context-sensitive, scalable solution relevant to infrastructure limitations and rapid population growth in Indonesian cities.

Thus, this research contributes by bridging theoretical optimization with practical implementation challenges in Jakarta. Beyond its practical contribution to the development of the HSCN, this study also holds implications for the field of computer science through the integration of mathematical modeling, Python-based numerical programming, and optimization algorithms within the context of smart energy systems. This interdisciplinary approach opens new opportunities for the development of data-driven and spatially informed Decision Support Systems (DSS) to aid energy transition planning and policy-making.

2. RESEARCH METHOD

This study designs three implementation periods for hydrogen vehicles: 2026-2030, 2031-2035, and 2036-2040. The projected hydrogen vehicle demand, as shown in Table 1, is derived from the official document *Indonesia Hydrogen Roadmap* (2023), which was prepared by the Indonesia Fuel Cell and Hydrogen Energy (IFHE) and Badan Riset dan Inovasi Nasional (BRIN). The roadmap outlines phased targets for hydrogen energy deployment based on Indonesia's long-term decarbonization goals. These projections implicitly assume an optimistic adoption rate of hydrogen vehicles supported by policy enforcement, infrastructure development, and declining hydrogen production costs over time. Although the roadmap does not explicitly quantify policy instruments, it presumes consistent regulatory support, coordination across sectors, and alignment with broader national energy transition strategies.

Since this research focuses on Jakarta, national projections were adjusted proportionally using vehicle population data from Badan Pusat Statistik (BPS) in 2023, which shows that approximately 20.98% of Indonesia's total vehicle population is concentrated in Jakarta. This proportion was used to estimate Jakarta's projected hydrogen vehicle demand for each planning period, as presented in Table 3.

Table 1. Projected Adoption of Hydrogen Vehicles in Indonesia

Period	2026-2030	2031-2035	2036-2040
Total Demand of Hydrogen Vehicles (Units)	3,000	20,280	115,128
Hydrogen Source	1) Grey-H_2 2) Co-firing 3) Blue-H_2 4) Green-H_2	1) Co-firing 2) Blue-H_2 3) Green-H_2	1) Blue-H_2 2) Green-H_2

Source: Indonesia Hydrogen Roadmap (2023)

This study uses an adapted gravity model and MILP to address the dual challenges of spatial planning and cost optimization in the HSCN. The models are implemented in Python using Pyomo and solved via Gurobi [23]. Figure 1 illustrates the Research Process Flow, outlining the step-by-step approach used in this study to optimize the HSCN, starting from pre-eliminating suitable gas station locations using a scoring method, followed by optimization with MILP, and concluding with a sensitivity analysis. The following section provides a detailed explanation of the methods used in this research:

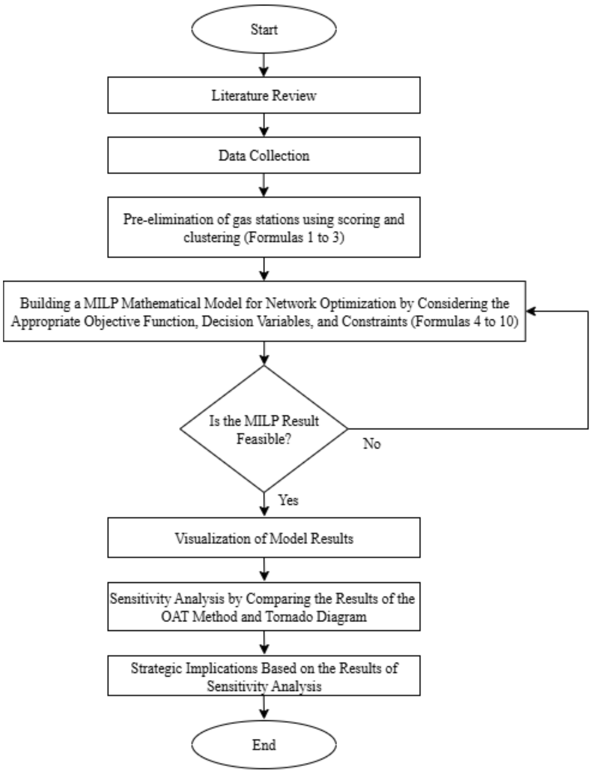

Figure 1. Research Process Flow

1. First, to identify suitable locations for HRS development, a pre-elimination step is conducted using a gravity-based scoring model. This model ranks 216 existing gas stations in Jakarta by calculating a potential score for each location. The scoring process is designed to streamline the analysis and improve efficiency by grouping gas stations based on their potential, which is determined using demographic indicators (such as population density and growth rate) and spatial accessibility [24].

   The potential of a gas station location *i* is calculated by considering its spatial interaction with other locations *j*, where the attractiveness of each location *j* (based on demographic factors) is divided by the square of the geographic distance between *i* and *j*. This approach is formalized in Equation (1), which is adapted from the gravity model used in spatial analysis [25]:

$$\text{Potential Score}_{\text{i}} = \sum_{j \neq i} \frac{A_j}{G_{ij}^2} \quad (1)$$

   Where:
   $Potential\ Score_i$: the potential of gas station location *i* as a candidate site for HRS development.
   A_j : the attractiveness of location *j*, which is calculated based on demographic factors.
   G_{ij} : the geographic distance between location *i* and location *j*.

   To compute G_{ij}, the Haversine formula is applied, which accurately measures the distance between two points on Earth based on their latitude and longitude while accounting for the planet's curvature [26]. This is particularly important in urban-scale studies such as Jakarta. The formula is presented in Equation (2):

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$$G_{ij} = 2r \cdot arc\sin(\sqrt{sin^2(\frac{\Delta\varphi}{2}) + \cos(\varphi_1) \cdot \cos(\varphi_2) \cdot sin^2(\frac{\Delta\lambda}{2})}) \quad (2)$$

Where:
r : Radius of the Earth (6,371 km).
φ : Latitude (Y coordinate) in radians.
λ : Longitude (X coordinate) in radians.
$\Delta\varphi$: Difference in latitude = $\varphi_i - \varphi_j$.
$\Delta\lambda$: Difference in longitude = $\lambda_i - \lambda_j$.

After calculating the potential scores, the results are clustered to facilitate interpretation and prioritization. The potential scores are grouped into several clusters to distinguish locations with very high to very low potential. The number of clusters is determined using the K-Means method [27]. The output is a priority cluster classification that supports a three-period planning scenario. The following Rule of Thumb is applied [28]:

$$k \approx \sqrt{n/2} \quad (3)$$

Where:
k : Number of clusters
n : Number of sub-districts (kecamatan)

2. Second, the MILP method is employed to optimize the HSCN by minimizing the total cost. MILP is a mathematical approach that allows for the simultaneous consideration of both continuous decision variables (e.g., quantities of hydrogen) and binary variables (e.g., whether a HRS is built at a specific location). This method is chosen because of its ability to handle complex systems that involve multiple factors and constraints. Specifically, it helps minimize the total costs associated with HRS capital and operational costs, hydrogen distribution via truck transportation, and carbon emission taxes. MILP is particularly effective for allocation and distribution problems involving multiple interconnected components, such as suppliers, HRS locations, and transportation routes, ensuring that hydrogen demand is met at the lowest possible cost [29].

The MILP model aims to find the optimal combination of decisions, balancing the various cost elements while adhering to constraints such as land-use limitations, hydrogen supply capacities, and demand fulfillment. This approach is efficient in providing an optimal solution by minimizing the overall costs across the HSCN. The formulation of the MILP model involves defining an objective function to minimize the total cost, decision variables to determine the best course of action, constraints to account for system limitations, and the assumptions used in the model [30]. Each of these components is described below:

a. Objective Function

$$\text{Minimization } Z = \left[\sum_{j\in J} Y_j \cdot (C_{cap} + C_{op}) + \sum_{i\in I} \sum_{j\in J} X_{ij} \cdot (Rtr_{ij} + Cem_{ij})\right] \quad (4)$$

Where:
I: Set of hydrogen suppliers
J: Set of potential HRS locations

b. Decision Variables
X_{ij} : Equals 1 if supplier *i* delivers hydrogen to HRS *j*, and 0 otherwise
Y_j : Equals 1 if an HRS is built at location *j*, and 0 otherwise.

c. Constraints

i. Cluster priority based on pre-elimination results.
$Y_j = 0 \quad \forall j \in J$, if Gas station$_j$ ∉ does not belong to the permitted cluster in a given period (5)

Table 2. Cluster Priority in a Given Period

Periods	Permitted Clusters
2026–2030	0 (Very High), 1 (High)
2031–2035	0, 1, and 2 (Medium)
2036–2040	0, 1, 2, dan 3 (Low)

ii. The total capacity of all constructed HRS must meet the total hydrogen demand.

$$\sum_{j\in J} Y_j \cdot Caphrs \geq D_{total} \quad (6)$$

iii. Each supplier must not exceed its maximum hydrogen production capacity.

$$\sum_{j\in J} Caphrs \cdot X_{ij} \leq Capsup_i \quad \forall i \in I \quad (7)$$

iv. Each HRS must be supplied by exactly one supplier.

$$\sum_{i\in I} X_{ij} = Y_j \quad \forall j \in J \quad (8)$$

If a gas station is not chosen as an HRS location ($Y_j = 0$), then no supplier is allowed to deliver hydrogen to that site.

v. Transportation decisions are only allowed if an HRS is constructed.

$$X_{ij} \leq Y_j \quad (9)$$

This refers to the transportation of hydrogen (via truck) from the supplier to the HRS.

vi. Binary variables.

$$X_{ij}, Y_j \in \{0, 1\} \quad (10)$$

These are decision variables that can only take two values: 0 or 1. In this model, binary variables are used to determine whether an HRS is built at a given location (1 if yes, 0 if no) and whether a supplier provides hydrogen to an HRS (1 if yes, 0 if no).

Where:
$Capsup_i$: Maximum hydrogen production capacity of supplier i
Caphrs : Maximum daily capacity of an HRS
C_{cap} : Capital cost per unit HRS
C_{op} : Operational cost per unit HRS (including maintenance, labor wages, hydrogen procurement costs and energy consumption).
C_{em} : Emission tax cost
R_{tr} : Truck rental cost from supplier i to HRS j
D_{total} : Total daily hydrogen demand in Jakarta

d. Model Assumptions

The MILP model relies on several simplifying assumptions to enhance computational tractability and focus the analysis on strategic infrastructure planning. First, the capital and operational costs of HRS are assumed to be uniform across all locations, regardless of local conditions. Each HRS is designed with a fixed maximum daily distribution capacity of 760 kg of hydrogen. It is further assumed that each HRS is supplied by a single hydrogen producer, while each producer may serve multiple HRSs up to its maximum daily production capacity.

The model treats total hydrogen demand in Jakarta as a fixed aggregate value that must be fully met without allowing for spatial demand variations across sub-districts. Truck rental costs and carbon taxes are calculated solely based on fixed distance rates between suppliers and HRS locations, with no consideration for inflation or dynamic pricing. All costs are treated as linear and deterministic. Moreover, the number of hydrogen suppliers and their production capacities are held constant throughout the analysis. These assumptions reflect a deterministic and linear model structure that prioritizes clarity and scenario comparability over dynamic complexity.

3. Sensitivity analysis is conducted using the One-at-a-Time (OAT) method to identify which parameters have the most significant influence on the outcomes of the MILP model. By comparing the results from each parameter variation with the baseline scenario, this approach helps determine the model's sensitivity and pinpoint the most influential factors [31]. To define the extent of parameter variation, a structured scale is applied [32]. In anticipation of potential uncertainties in hydrogen vehicle adoption, sensitivity analysis is also extended to assess fluctuations in demand. Five variation scenarios are evaluated relative to the baseline: 0.5×, 0.75×, 1.0×, 1.25×, and 1.5× [33]. This allows the study to quantify the impact of demand changes on both the number of HRS constructed and the total cost, offering more robust insights for medium and long-term planning under uncertainty.

In addition to the OAT approach, this study also employs Tornado Diagram Analysis to strengthen the sensitivity assessment. While OAT provides insights into how model outputs change across different parameter scales, the tornado diagram offers a comparative visualization of the relative impact of each parameter on total cost [34]. This dual-method sensitivity analysis enhances the robustness of the findings by balancing depth through OAT and clarity through the Tornado Diagram.

To validate the model's structure and logic, the design aligns with key planning objectives of the Indonesia Hydrogen Roadmap and is cross-checked for consistency with real-world constraints, such as land-use limitations, demand growth, and supplier proximity. Although empirical validation is currently limited due to the early-stage development of hydrogen infrastructure in Indonesia, the model's cost parameters are benchmarked against international studies, providing a reasonable basis for conceptual validity.

3. RESULTS AND DISCUSSION

This chapter discusses the results concerning the pre-elimination of potential HRS locations, optimization using MILP, and sensitivity analysis. The explanation of that hybrid framework is provided below:

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3.1. Pre-elimination of Potential HRS Locations

The pre-elimination stage uses a gravity-based scoring model to rank 216 existing gas stations based on the previously described formulas, with the implementation scripted in Python. Figure 2 presents the results of the pre-elimination along with the cluster visualization.

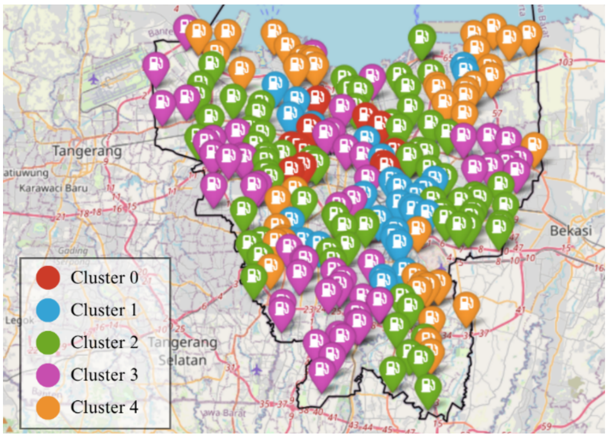

Figure 2. Visualization of Clusters from the Pre-elimination Process

Based on the scoring and clustering results, five clusters were formed ranging from very high scores (Cluster 0: most potential) to very low scores (Cluster 4: least potential). As shown in Figure 2, gas station 34.112.01 located in Tambora Subdistrict has the highest potential score and falls into Cluster 0, representing the group with the highest priority for HRS development. Gas station in Palmerah Subdistrict is also categorized in Cluster 0, indicating very high demographic and geographic attractiveness in the area, making them prime candidates for hydrogen infrastructure development in West Jakarta. Additionally, gas station in Kemayoran (Central Jakarta) and Matraman (East Jakarta) also belong to Cluster 0, thus becoming priorities for HRS development.

Furthermore, gas station in Jatinegara and Kramat Jati (East Jakarta), Senen (Central Jakarta), Koja (North Jakarta), Tebet and Kebayoran Baru (South Jakarta), and Grogol Petamburan (West Jakarta) show high potential, categorized in Cluster 1. This position indicates that several gas stations located in these subdistricts are worthy of consideration as strategic locations for HSCN development. Conversely, areas such as Kebayoran Lama (South Jakarta), as well as Kelapa Gading and Penjaringan (North Jakarta), where most gas stations fall into Cluster 4, indicate that demographic and geographic factors in these regions are less favorable for HRS development compared to other locations. These classification results will be used in MILP data processing as the focus for integrating gas station with HRS, following the potential scores and clusters, covering areas with the highest potential impact and utilization.

3.2. Optimization using Mixed-Integer Linear Programming (MILP)

At this stage, a mathematical modeling approach is employed to determine the locations for constructing HRS and the distribution of hydrogen suppliers to each HRS site. The MILP model is formulated to minimize the total cost within the HSCN, encompassing capital costs for HRS construction, daily operational costs, truck rental costs for transportation of hydrogen, and carbon emission taxes arising from transportation processes. The model also includes several constraints, such as cluster priority for phased HRS development, HRS capacity limits, production capacity of each supplier, and hydrogen demand across the entire Jakarta.

The model implementation is carried out using Python, leveraging the Gurobi optimization library. The following presents the optimization results for the three planning periods based on the previously developed mathematical model.

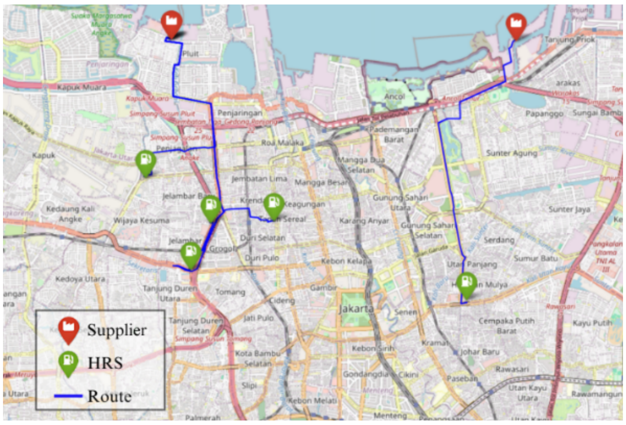

Figure 3. HSCN Visualization Results for 2026-2030 Period

The 2026-2030 period was designated as the initial phase for the implementation of the HSCN in the Jakarta. In this stage, a conservative approach was adopted by considering only gas stations categorized under high-priority clusters namely, Cluster 0 and Cluster 1 based on the results of the prior pre-elimination process. A total of five HRS were selected, with the spatial distribution of these locations predominantly concentrated in Central Jakarta and West Jakarta. These results indicated that the model not only prioritized numerical optimization but also incorporated the geostrategic suitability of the city into its decision-making process. Furthermore, the selection of PLTGU Muara Karang and PLTGU Priok as the main hydrogen suppliers reflected the system's preference for sources with spatial proximity to distribution points, aiming to minimize both logistics costs and environmental impact.

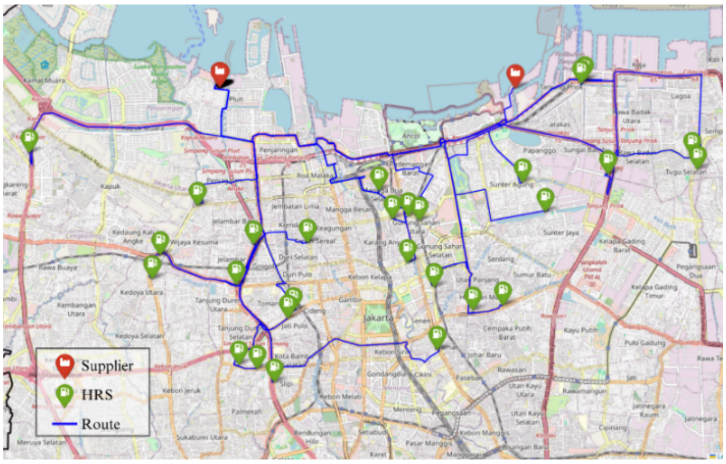

Figure 4. HSCN Visualization Results for 2031-2035 Period

The 2031-2035 period represented a transitional phase from a limited HSCN to a medium-scale system. Assuming a rapid increase in hydrogen vehicle penetration during this period, hydrogen demand rose significantly. As a result, the model expanded the range of potential locations by including gas stations from Cluster 2. The optimization results identified 28 gas stations selected for integration with HRS, an increase of more than fivefold compared to the initial phase. Spatially, the distribution of HRSs extended to broader administrative areas, including East and South Jakarta. This distribution pattern indicated that the network expansion ensured access to hydrogen distribution in previously underserved high-density areas. The selected suppliers continued to be dominated by PLTGU Priok and PLTGU Muara Karang. The consistent selection of these two suppliers demonstrated that their location and production capacity remained sufficient to meet the demand of multiple HRS locations without causing bottlenecks.

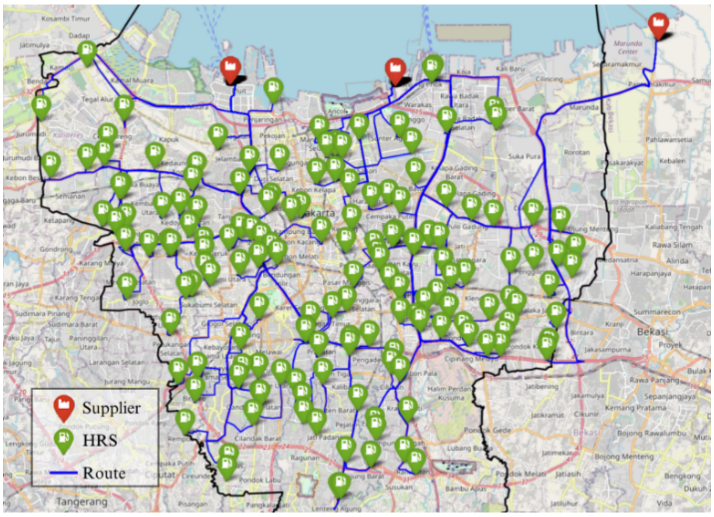

Figure 5. HSCN Visualization Results for 2036-2040 Period

In the 2036-2040 period, with projected hydrogen demand continuing to rise, the system was required to operate at full scale. In this phase, Clusters 0 through 3 were considered as candidate locations for HRS development. The optimization results identified 159 gas stations selected for integration with HRSs, representing an almost fivefold increase from the previous period. The spatial distribution of HRSs during this phase was evenly spread across all regions of Jakarta. This outcome indicated that the system had achieved a balance between cost efficiency, area coverage, and supply capacity. From a cost structure perspective, the values remained proportional, and the model-maintained efficiency despite the expanded scale.

A noteworthy development in this period was the inclusion of the PLTGU Muara Tawar as an additional hydrogen supplier. Its entry reflected that the capacities of the previously selected suppliers PLTGU Priok and PLTGU Muara Karang were no longer sufficient. The proximity of PLTGU Muara Tawar to several HRS locations offered a more optimal solution. The utilization of PLTGU Muara Tawar to serve East Jakarta demonstrated that the system had strategically expanded both its service area and supply network. This confirmed the model's adaptability to rising demand while maintaining cost-effectiveness through the integration of new supply sources.

Following the results obtained from the three planning periods, a comparative analysis was conducted to provide a comprehensive overview of the development in the number of HRS units constructed and the total minimum cost for each period. Table 3 presents the modeling data, including total demand for hydrogen vehicles in Jakarta, the number of selected HRSs, total cost, and average cost per HRS unit for each period. Furthermore, Figure 6 illustrates the visual trend of changes in the number of HRSs and total costs across the planning horizon, facilitating a clearer understanding of the scale and cost dynamics over time.

Table 3. Comparison of Results Across Periods

Periods	Total Demand in Jakarta (Units)	Number of HRS	Total Cost (IDR)	Cost per HRS (IDR)
2026-2030	630	5	57,870,880,000	11,574,176,000
2031-2035	4,255	28	324,078,500,000	11,574,232,142
2036-2040	24,157	159	1,840,399,000,000	11,574,836,478

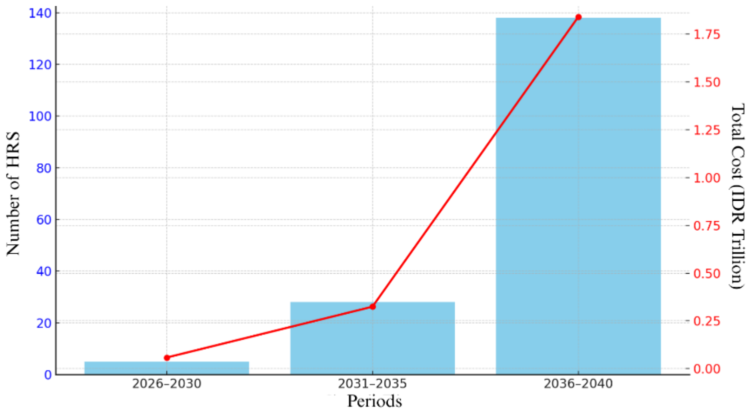

Figure 6. Comparison of Number of HRS and Total Cost

Based on Table 3, it can be observed that the HSCN demonstrated excellent scalability. Although the number of HRS units increased significantly from 5 to 159, the average cost per unit remained relatively constant. This indicates that the system was able to respond to growth effectively without compromising operational efficiency. Cost stability is essential for long-term planning, as it ensures that investments continue to deliver optimal economic value. Moreover, these results confirm that the MILP method used in this study was effective in simultaneously managing location and production capacity variables.

In addition, the inclusion of a new supplier PLTGU Muara Tawar highlighted the need for a system designed to be adaptive and flexible. The model must be capable of anticipating future supplier integration to avoid capacity bottlenecks. Therefore, these findings can serve as the basis for strategic recommendations in the development of future hydrogen energy infrastructure, particularly in densely populated urban areas such as Jakarta.

The spatial expansion and supplier diversification modeled in this study also align with the national objectives outlined in the Indonesia Hydrogen Roadmap. Jakarta's case demonstrates how phased infrastructure deployment, starting with high-priority urban clusters and gradually extending coverage can support broader decarbonization goals without overwhelming financial resources. These results reinforce the strategic importance of integrating HRS within existing gas infrastructure to overcome land-use constraints and accelerate early-stage adoption.

Nevertheless, the model has several limitations that must be acknowledged. It assumes homogenous demand distribution across Jakarta and does not consider local variation at the sub-district level. Additionally, capital and operational costs are treated as fixed and uniform, overlooking site-specific differences. The deterministic nature of the model also means it does not incorporate uncertainty in demand forecasts, cost fluctuations, or policy enforcement levels. These simplifications, while necessary for computational efficiency, may affect the model's applicability in highly dynamic or uncertain planning contexts.

3.3. Sensitivity Analysis

This sensitivity analysis aims to evaluate how changes in key model parameters influence the two main outcomes: the total cost and the number of HRS to be constructed. Two complementary methods are employed: the OAT approach and the Tornado Diagram Analysis. The OAT method assesses model behavior by varying each parameter independently across five levels (0.5×, 0.75×, 1.0×, 1.25×, and 1.5×) relative to the baseline, allowing for detailed trend observations. Meanwhile, the tornado diagram provides a comparative visualization of the relative impact of each parameter by focusing on the output variation between the lowest (0.5×) and highest (1.5×) values. Table 4 summarizes the key parameters considered in the analysis.

Table 4. Sensitivity Analysis Parameters

Parameter	Description
HRS Daily Capacity	760 kg hydrogen per day
Total Demand	Based on projections according to the planned years
HRS Capital Cost	Uniform for all HRS units
HRS Operational Cost	Daily, constant for all locations
Truck Rental Cost	Dependent on the distance between suppliers and HRS
Carbon Tax Cost	Based on the distance between suppliers and HRS

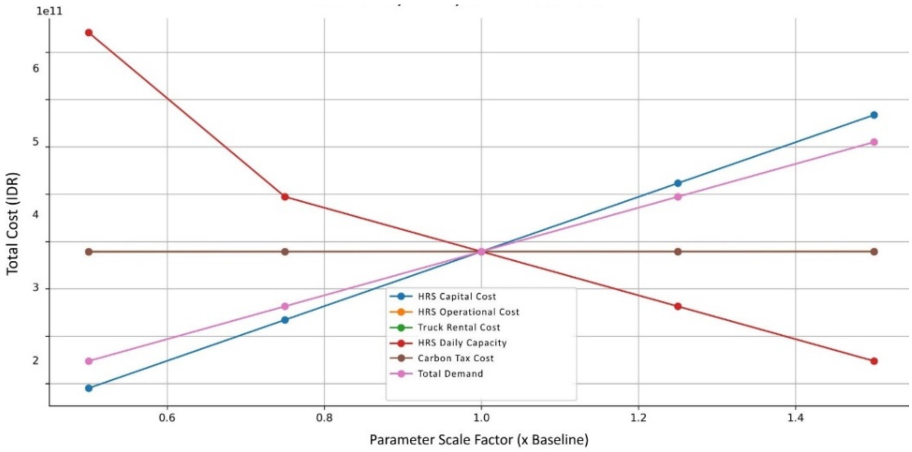

Figure 7 OAT Sensitivity Analysis on Total Cost

Based on Figure 7, the results indicate that HRS daily capacity has a significant impact on the total cost. When the capacity is increased from 0.5× to 1.5×, the total cost drastically decreases from approximately IDR648,168,634,406 to IDR219,909,000,132. The baseline scenario (1.0×) results in a cost of IDR324,078,514,064. This nonlinear relationship suggests that even small changes in daily capacity can lead to substantial cost fluctuations. Therefore, strict control and careful planning of this parameter are essential to maintain economic feasibility.

Similarly, total demand is highly sensitive. An increase in demand from 0.5× to 1.5× causes the total cost to surge from IDR162,037,574,465 to IDR486,122,338,064. With a baseline cost of IDR324,078,514,064, it is evident that this parameter plays a crucial role in determining financial outcomes, and thus requires close attention in infrastructure planning. In contrast, HRS Capital Cost, despite having no effect on the number of HRS units built (which remains constant at 28), directly influences the total cost. As capital cost increases from 0.5× to 1.5×, the total cost rises significantly from IDR162,379,214,064 to IDR485,777,814,064. The nearly linear trend confirms the parameter's direct economic impact on the system, emphasizing the need to optimize investment costs.

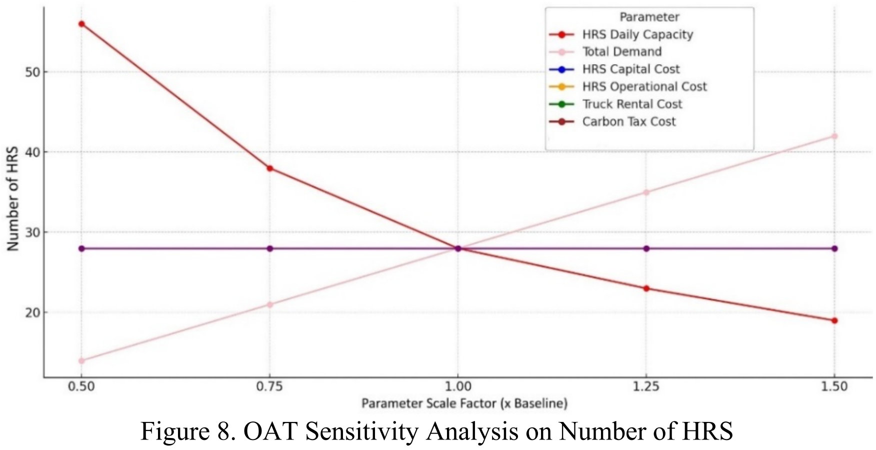

Figure 8. OAT Sensitivity Analysis on Number of HRS

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Based on Figure 8, the HRS daily capacity parameter shows a strong inverse relationship with the number of HRS constructed. Increasing the capacity from 0.5× to 1.5× results in a sharp decline in the number of stations, from 56 units down to just 19. The nonlinear pattern of this decline suggests that increasing capacity has diminishing marginal returns in terms of reducing infrastructure requirements, making it a critical factor in system configuration. Conversely, total demand demonstrates a strong positive correlation with the number of HRS units. As demand increases from 0.5× to 1.5×, the number of HRS built rises significantly from 14 to 42 units. This highlights how demand directly shapes infrastructure development and underscores the importance of accurate demand forecasting.

Based on the OAT sensitivity analysis of six parameters, it was concluded that the three most influential factors affecting the total cost were daily HRS capacity, total hydrogen demand, and HRS capital cost. These factors directly determined the optimal configuration of HRS quantity and the scale of infrastructure required. Meanwhile, parameters such as operational costs, truck rental costs, and carbon tax had relatively minor impacts on total cost.

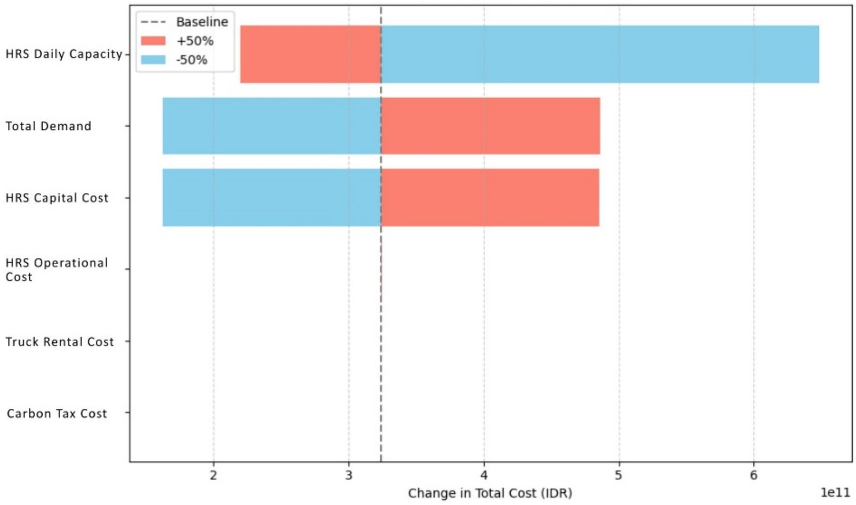

Figure 9. Tornado Diagram Analysis on Total Cost

To further test the model's robustness, a Tornado Diagram was constructed using the same parameter variations applied in the OAT analysis. While OAT enabled detailed assessment of individual parameter effects across five scales, the tornado diagram highlights the relative importance of each parameter on the total cost. As shown in Figure 9, daily HRS capacity, total hydrogen demand, and capital cost were the most impactful parameters, confirming earlier observations from the OAT results.

Interestingly, while OAT results showed nuanced trends such as diminishing returns or nonlinear responses in some parameters, the tornado diagram offered a clearer ranking of sensitivity magnitude. This comparative analysis confirms that infrastructure decisions should prioritize accurate forecasting of demand and tight control over capital budgeting. Less sensitive parameters, such as carbon tax and truck rental, had marginal effects and can be considered secondary in short-term strategic planning.

3.4. Strategic Implications

Based on the results of the sensitivity analysis, several strategic policy recommendations can be formulated to support the development of a robust and sustainable HSCN in Indonesia. Key parameters such as HRS capacity, hydrogen demand, and capital cost have demonstrated substantial influence on the system's performance and total investment requirements. Therefore, national planning efforts should prioritize effective standardized infrastructure capacity, demand forecasting, and cost optimization strategies. The following recommendations outline several actionable measures that align with these priorities. First, the government should consider establishing minimum technical standards for HRS capacity [35], given that this parameter exhibited the most significant influence on both infrastructure scale and cost efficiency. Consistency in technical capacity will allow better forecasting and reduce unnecessary investment fragmentation. Second, hydrogen demand projections must be continuously updated and realigned with the national hydrogen roadmap to minimize the risks of infrastructure under-utilization or over-supply [36]. Dynamic and data-driven demand forecasting is essential for long-term planning accuracy.

Additionally, capital expenditure for HRS development another highly sensitive factor can be mitigated through policy interventions such as fiscal incentives, targeted subsidy schemes, or the facilitation of public-private partnerships [37], [38]. These financial instruments can ease the investment burden, particularly in the early stages of deployment. Although operational costs, transport-related costs, and carbon tax impacts were found to be relatively minor, they should not be neglected entirely. These factors still contribute to the broader sustainability goals and environmental accountability of hydrogen logistics.

By integrating these strategic considerations, the future hydrogen supply chain network in Indonesia can be developed in a way that is not only economically viable but also responsive to policy targets, environmental standards, and urban infrastructure constraints. This integrated approach ultimately supports a smoother transition toward clean and sustainable transportation systems.

4. CONCLUSION

Based on these findings, this study concludes that the integrative approach combining site pre-elimination using a modified gravity-based scoring model and optimization through MILP offers a significant contribution to HSCN planning. The scoring method successfully identified and classified 216 existing gas stations in Jakarta into five clusters based on spatial and demographic potential, with Clusters 0 and 1 (very high and high priority) selected for initial HRS development. The MILP optimization model effectively determined the optimal HRS locations and hydrogen supply distribution from suppliers to stations to meet projected hydrogen vehicle demand from 2026 to 2040, while considering capital, operational, logistics, and carbon emission costs. The optimization results showed a gradual increase in the required number of HRS units: 5 units in 2026-2030, 28 units in 2031-2035, and 159 units in 2036-2040, with a relatively stable system cost averaging approximately IDR 11.57 billion per HRS unit. Sensitivity analysis revealed that the most influential parameters on the number and distribution of HRSs were HRS operational capacity, total daily hydrogen demand, and capital investment cost. Overall, the integration of the adapted gravity model and MILP provides a strategic framework for planning HSCN in Indonesian urban areas, particularly by leveraging existing refueling infrastructure to address land and investment constraints.

Based on this research, future studies are recommended to enhance the quality and availability of spatial data, particularly regarding hydrogen demand and sub-district-level vehicle growth projections, to generate more geographically precise optimization outputs. In addition, future research should explore stochastic model extensions and real-world calibration techniques once broader deployment data becomes available, to improve the robustness and realism of the model. Then, the proposed model can be adapted and tested in other metropolitan areas in Indonesia with similar urban constraints, such as Surabaya, Bandung, or Medan, to assess its broader applicability. Beyond technical enhancements, it is also essential to incorporate non-economic aspects into the analysis, such as public perception of HRS safety, risks of hydrogen leakage, and potential regulatory barriers to construct a more comprehensive infrastructure roadmap. Furthermore, the environmental co-benefits of hydrogen adoption, including reductions in local air pollution and noise levels, should be quantitatively evaluated to strengthen the justification for a nationwide hydrogen deployment strategy. Integrating these technical, social, and environmental aspects will further elevate the model's relevance as a robust decision-support tool for policymakers and urban energy planners.

CONFLICT OF INTEREST STATEMENT

The Authors state no conflict of interest.

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