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Relative Efficiency Analysis for Solar Plant Location Using Data Envelopment Analysis Technique

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Abstract

In this study, the upstream process of the Green Hydrogen Supply Network (GHSC) is investigated, in which electricity from solar renewable energy is used in the electrolysis technique for the hydrogen production process. Initially, multiple criteria relevant to the solar plant location based on geographic, climate, and sun-earth interaction data are examined. In particular, seven input criteria are obtained from the area, the average air temperature, the average rainfall amount, the average precipitation days, the average relative humidity, the wind force, and the average yearly sunshine hours. Additionally, three output criteria are the population density, the direct normal irradiation, and the specific photovoltaic power output, respectively. Then, the case study of the state of Saxony-Anhalt in Germany inclusive of eleven districts and three independent cities is used as Decision-Making Units (DMUs), in which the Data Envelopment Analysis (DEA) technique is applied to explore each DMU's relative efficiency. The obtained results show that about 57 percent of all the DMUs are found to be relatively efficient. The outcome of the study can be used to analyze strategic policy for GHSC involving the upstream and other operations in future studies.

Keywords
Solar Plant Location, Multi-Criteria Decision Analysis, Data Envelopment Analysis, Green Hydrogen Supply

1. Introduction
An energy crisis is considered one of the significant bottlenecks in the supply of energy resources to an economy, where population growth is one of the key factors that has led to a surge in the global demand for energy in recent years. Fossil fuel energy, in particular, has served the world for decades. However, evidence has been shown that fossil fuel energy greatly contributes to the increase in GreenHouse Gas (GHG) emissions, which could negatively impact human life in the long run and thus is not sustainable (Jurasz et al. 2020). Thus, there is a growing interest in the renewed focus on reducing carbon emissions from fossil fuel usage, in which increased attention to renewable

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energy has also been observed. The global renewable energy market is also expected to continue its upward growth, in which the market will reach over two trillion U.S. dollars by 2030 as shown in Figure 1 (Statista 2023).

Solar thermal, wind, hydro, geothermal, and ocean energy are the renewable energy sources that are expected to further expand significantly shortly. Solar Photovoltaic Technology, for example, is found to be the type of renewable energy technology that is on track with the Net Zero Emissions by 2050 Scenario (Tsiropoulos 2020). Solar energy, in particular, is also one of the most sustainable ways reported for producing hydrogen energy by using solar energy to split water into hydrogen and oxygen via the electrolysis production technique. Thus, solar hydrogen is found to be promising for the green hydrogen economy as this method emits no Carbon dioxide (CO2) to produce hydrogen in the upstream process of the Green Hydrogen Supply Network (GHSC).

Existing studies point out that the extensive growth of the renewable energy market, the supply of solar energy capacity, and the demand for hydrogen energy could expedite the adaptability and strengthen GHSC soon (Sgarbossa et al. 2023, Hassan et al. 2024). Thus, in this study, we assess the upstream process of the GHSC based on the green hydrogen concept, in which electricity from a renewable energy source such as solar renewable energy can be used in the electrolysis technique to break down water into hydrogen and oxygen. Given that the problem of selecting a location for a solar renewable plant is concerned with multiple, conflicting criteria at a strategic level, this type of problem can be viewed as a type of Multi-Criteria Decision Analysis (MCDA) problem. Thus, one of the well-known MCDA techniques called Data Envelopment Analysis (DEA) is applied in this study to analyze the relative efficiency of location alternatives for solar energy plants.

In this study, multiple criteria relevant to the solar energy plant location based on geographic, climate, and sun-earth interaction data are examined. In particular, seven input criteria are obtained from the area, the average air temperature, the average rainfall amount, the average precipitation days, the average relative humidity, the average yearly sunshine hours, and the wind force. Additionally, three output criteria are the population density, the direct normal irradiation, and the specific photovoltaic power output, respectively. Then, the case study of the state of Saxony-Anhalt in Germany inclusive of eleven districts and three independent cities is used as Decision-Making Units (DMUs), in which the Data Envelopment Analysis (DEA) technique is applied to explore each DMU's relative efficiency. We note that this is the first phase of our ongoing studies to model and analyze GHSC involving upstream, midstream, and downstream operations in the GHSC research plan.

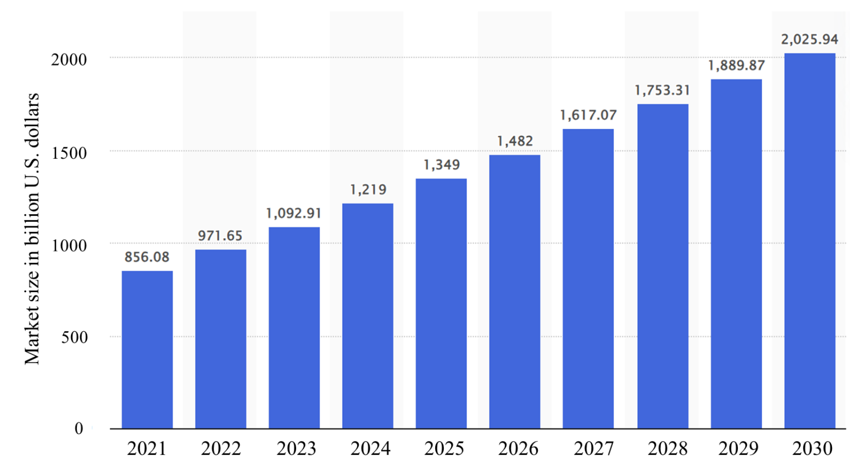

Figure 1. The expected global renewable energy market (Statista 2023)

1.1 Objectives

The objectives of this study are to collect data relevant to multiple criteria related to geographic, climate, and sun-earth interaction data for the location selection problem of solar energy plants and to analyze alternatives under evaluation of the case study using one of the well-known MCDA techniques called DEA. In particular, the DEA technique can be used to not only assess the efficiency of each potential solar energy plant location but can also classify benchmarking locations. The applied DEA methodology is used to evaluate the case study of the state of Saxony-Anhalt in Germany, which can then later be verified and validated with existing locations of solar energy farms and plants in the case study. It is thus expected that the outcome of the study can be used as a guideline to examine the strategic policy for GHSC for practitioners and policymakers.

2. Literature Review

The hydrogen economy is considered an economy that relies on hydrogen as the commercial energy that can deliver a substantial portion of national energy and services. The concept of hydrogen energy is expected to become a reality when hydrogen produced from various renewable energy sources can be economically obtained and used in an environmentally friendly manner. In this study, the upstream process for GHSC is evaluated at a strategic-level decision to assess potential locations for solar energy plants. Thus, we highlight key existing literature and research challenges based on the concept of network design for GHSC and the locational model for GHSC as follows.

The utilization of hydrogen can improve the sustainability of the renewable energy system as well as the overall system flexibility (Kovač et al. 2021). The Hydrogen Council also expects that hydrogen could not only fulfill 18% of the world's energy demand but also lessen CO2 emissions by approximately 50%. Thus, hydrogen technology advancement from various energy sectors and effective logistics systems in the hydrogen network could help to increase operational flexibility and perform a pivotal function by linking infrastructures for future low-carbon energy systems. Nonetheless, the insufficiency of existing infrastructure is considered one of the hurdles to boosting the hydrogen economy. Thus, an investigation of large-scale infrastructure based on the proper assessment of country-wide strategies is needed (Hydrogen Council 2022).

Several studies in the literature suggest challenges in operational, tactical, and strategic-level decisions for hydrogen networks (Riera et al. 2023, Lee et al. 2024). The infrastructure of the hydrogen network typically starts from the energy sources and ends at the demand areas, in which various alternatives exist at each link of the infrastructure network (Figure 2). Concerning sources of hydrogen supply, conventional hydrogen production typically utilizes coal and biomass as sources for the production process. On the other hand, green hydrogen production in the GHSC is concerned with the electrolysis technique, in which water and electricity from renewable energy sources like wind and solar are used. The electrolysis process, in particular, is a promising technology to achieve an extensive deployment for low-carbon footprint in the energy system albeit currently an expensive option (Ren et al. 2024). Then, the produced hydrogen can be distributed using several modes depending on the physical forms of hydrogen such as liquid and gas. That is, liquefied hydrogen is typically transported in tankers via roads and railways, whereas gaseous hydrogen can be distributed via pipelines. In addition, storage decision is a vital function of the GHSC, which is also complex due to dissimilar physical forms of hydrogen. Thus, it is important to evaluate not only a decision at each operation, but also synthesize decisions together concerning the upstream, the midstream, and the downstream process, especially in the lacking area of GHSC. We next illustrate recent studies that emphasize key research gaps as follows.

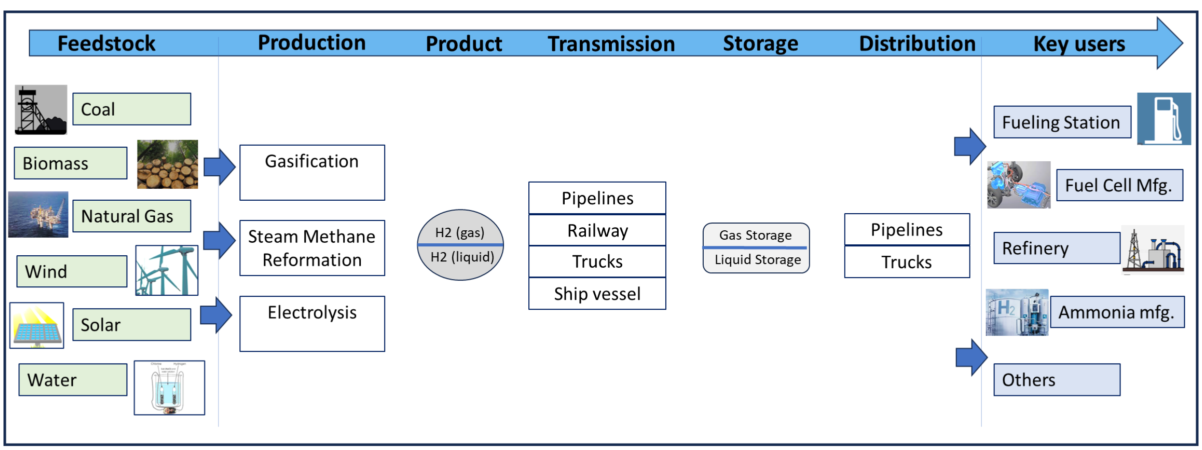

Figure 2. A schematic flow of the hydrogen supply chain

Liu and Ma (2020) suggest some research gaps and directions for GHSC. According to the authors, many problems have yet to be resolved from a technical perspective, such as the efficient storage of hydrogen at normal temperatures and pressures, the economic benefits engendered by market demand that could accelerate technological upgrades, and the introduction of a hydrogen energy system that can address human health, political conflict, and energy shortages to estimate and budget for its tangible benefits. Riera et al. (2023) conducted a review of hydrogen production and supply chain modeling and optimization and suggested lacking aspects in the literature. The authors point out that research gaps exist for production sources, international cases, and modeling methodology. That is, there is a need to consider water, natural gas, biomass, electricity, and critical material supply chains to ensure that hydrogen models have a realistic representation of the feedstocks available to produce the commodity. In addition, it is suggested to take an international perspective to allow decision-makers to more accurately model geopolitical climates. Moreover, the stochastic aspect of supply and demand is also needed to better capture the variability of renewable resources such as wind and solar and integrate them with hydrogen production. Sgarbossa et al. (2023) point out that modeling approaches both material flow-based and energy-based need to consider the whole renewable hydrogen network. The authors also note that the production of green hydrogen is strongly related to the availability and quality of feedstocks. The feedstock supply of hydrogen, such as solar and wind power for electricity, is often uncertain and thus should be further examined.

Existing studies also suggest that an assessment of GHSC involves multiple criteria and the application of MCDA for GHSC is called for (Rasul et al. 2022). For example, Oner and Khalilpour (2022) propose the evaluation model of green hydrogen carriers using MCDA. In particular, the authors evaluate different hydrogen carriers under criteria relevant to storage energy, density, technical readiness, reversibility, material handling, toxicity, safety, environmental impact, and cost. The authors apply the Analytic Hierarchy Process (AHP), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the VIekriterijumsko KOmpromisno Rangiranje (VIKOR) in their study and point out the importance of using integrated MCDA tools. Azadnia et al. (2023) examine and analyze the European region's green hydrogen supply chain risk factors by using an integrated Delphi method and the best-worst method. In particular, seven categories including economic, supply chain process and governance, technological and infrastructure, environmental, market, social, and policy and regulation are analyzed for associated risk factors. Ransikarbum et al. (2023) propose an integrative MCDA tool using AHP, fuzzy AHP, and DEA techniques to analyze weighted criteria and sourcing alternatives using data collected from a group of selected experts in Thailand. A list of criteria related to sustainability paradigms and sourcing decisions for the possible use of hydrogen energy, including natural gas, coal, biomass, and water, are evaluated in their study.

Research studies related to location analysis in the realm of GHSC are also scarce in the literature. Lin et al. (2020) conducted a review of hydrogen station location models. The authors suggest that the lack of hydrogen stations is a major barrier to the introduction of hydrogen vehicles. Furthermore, given the high cost of constructing hydrogen stations, it is desirable to build as few stations as possible while still adequately serving consumers. Mostafaeipour et al. (2020) investigate the solar-powered hydrogen potential and location planning for big cities in Iran. Several criteria are used in their study inclusive of solar radiation, wind speed, air temperature, precipitation, dust, altitude, region's population, cloudiness, and humidity. Almutairi (2022) investigated an economic investigation of wind-hydrogen projects using a case study in Iran. Six major criteria related to annual electricity production, annual hydrogen production, CO2 emission reduction, capacity, levelized cost of the energy, and levelized cost of the hydrogen are included in their study.

Thus, it is evident that research gaps exist in the realm of location analysis for GHSC that involves multiple criteria based on a particular geographic region. In this study, we highlight the application of the DEA technique for evaluating solar energy plants under multiple criteria using a case study in Germany. We note that this is the first phase of our ongoing studies to compare and contrast policies between Germany and Thailand case studies in the GSHC framework and to model the GHSC network involving the upstream, the midstream, and the downstream operations.

3. Methodology

In this study, one of the well-known MCDA techniques called DEA is applied to evaluate the solar energy plant location under multiple, conflicting criteria. MCDA, in particular, is considered a sub-discipline of operations research that explicitly evaluates multiple conflicting criteria in decision-making. Other commonly interchangeable terminologies include multiple attribute utility theory, multiple attribute value theory, multiple attribute preference theory, and multi-objective decision analysis. Recent studies in the realm of MCDA suggest that integration among MCDA tools is needed to account for the disadvantages of each particular tool alone (Nannar et al. 2024). Additionally, uncertainty such as fuzzy theory should also be integrated with MCDA tools (Ransikarbum and Kim 2024, Wattanasaeng and Ransikarbum 2024).

The DEA technique, in particular, is a type of multi-criteria productivity analysis model that utilizes the production theory-based nonparametric approach for relative efficiency analysis. Alternatives in DEA analysis are often referred to as DMUs and are evaluated under the input and output criteria. The main aim of DEA is to also explore benchmarking guidelines for inefficient DMUs of interest and has been proven useful in several application areas (Ransikarbum and Kim 2017, Ransikarbum and Pitakaso 2021, Ransikarbum et al. 2022). Advantages of DEA also include the capability to handle multiple input and output criteria and the capability for inter-criteria comparison with actual units of criteria. The development of the DEA model involves two scale assumptions known as Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). In particular, the CRS assumption reflects the fact that output will change by the same proportion as inputs are changed, whereas the VRS reflects the fact that production technology may exhibit increasing, constant, and decreasing returns to scale. In this study, the VRS assumption is used in the analysis given that there are reasonable differences in terms of scales for various DMUs under investigation.

A DEA model can also be modeled with input or output orientation. That is, the output-oriented DEA model will attempt to maximize output for a given level of input (i.e., the model analyses how much a DMU can increase its output for a given level of input). In contrast, the input-oriented DEA model will minimize input for a given level of output (i.e., the model indicates how much a DMU can decrease its input for a given level of output). The general model for the output-oriented DEA model is non-linear as illustrated in Equations (1) – (4), where the objective function is to maximize the ratio of the weighted sum of the outputs to the weighted sum of the inputs (Model 1). Then, given the non-linear form of the DEA model, the non-linear term can be transformed and converted into the linear programming problem as presented in Equations (5) – (9) (Model 2). Analyzed DMU will be considered efficient if it obtains a score of one, whereas scores that are lesser than one imply relative inefficiency. Moreover, more than one alternative may be found to be efficient, which can serve as benchmarking guidelines for inefficient DMUs for further improvement. Additionally, the input-oriented DEA model with the VRS assumption is illustrated as shown in Equations (10)-(15), respectively (Model 3) (Xu et al. 2020).

(Output-oriented DEA model)

Sets

I : Set of input criteria, indexed by i

J : Set of output criteria, indexed by j

K : Set of DMUs, indexed by k

Parameters

x_{i,k_0} : Amount of input data for the input i of the DMU k

y_{j,k_0} : Amount of output data for the output j of the DMU k

Decision variables

U_i : The weight assigned to the input i

V_j : The weight assigned to the output j

(Model 1)

$$Maximize\ \ Efficiency\ \frac{\sum_{j \in J} y_{j,k_0} V_j}{\sum_{i \in I} x_{i,k_0} U_i} \tag{1}$$

$$Subject\ to: \quad \frac{\sum_{j \in J} y_{j,k} V_j}{\sum_{i \in I} x_{i,k} U_i} \leq 1 \ ; \forall k \in K \tag{2}$$

$$U_i \geq 0 \ ; \forall i \in I \tag{3}$$

$$V_j \geq 0 \ ; \forall j \in J \tag{4}$$

(Model 2)

$$Maximize\ Efficiency \sum_{j \in J} y_{j,k_0} V_j \tag{5}$$

$$Subject\ to: \quad \sum_{i \in I} x_{i,k_0} U_i = 1 \tag{6}$$

$$\sum_{j \in J} y_{j,k} V_j - \sum_{i \in I} x_{i,k} U_i \leq 0 \ ; \forall k \in K \tag{7}$$

$$U_i \geq 0 \ ; \forall i \in I \tag{8}$$

$$V_j \geq 0 \ ; \forall j \in J \tag{9}$$

(Input-oriented DEA model)

Sets

I : Set of input criteria, indexed by i

J : Set of output criteria, indexed by j

K : Set of DMUs, indexed by k

Parameters

x_{i,k_0} : Amount of input data for input i of DMU k

y_{j,k_0} : Amount of output data for output j of DMU k

Decision variables

λ_k : The dual variable assigned to DMU k

θ : The scalar value for the efficiency score

(Model 3)

$$Minimize\ Efficiency\ \theta \tag{10}$$

$$Subject\ to: \quad \sum_{k \in K} \lambda_k x_{i,k} \leq \theta x_{i,k_0} \ ; \forall i \in I \tag{11}$$

$$\sum_{k \in K} \lambda_k y_{\mathrm{j},k} \geq y_{\mathrm{j},k_0} \ ; \forall j \in J \tag{12}$$

$$\sum_{k \in K} \lambda_k = 1 \tag{13}$$

$$\lambda_k \geq 0 \ ; \forall k \in K \tag{14}$$

$$\theta \geq 0 \tag{15}$$

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4. Case Study

4.1 Decision-Making Units (Alternatives)

We next discuss the problem statement relevant to the selection problem for solar energy plant location using the case study of the state of Saxony-Anhalt in Germany. The state of Saxony-Anhalt comprises eleven districts and three independent cities (Table 1) and is considered the eighth-largest state in Germany. The largest district in the state is the Stendal district, whereas the smallest district is the Burgenland district. Additionally, the three independent cities in the state also have the highest population density in the state. In this study, all the districts and independent cities are chosen as alternatives for the assessment, which can also be illustrated as shown in Figure 3.

Table 1. Description of decision-making units (Alternatives) for the case study

Alternative (DMU)	Description	Area (km^2)	Density	Latitude, Longitude
D1	Altmarkkreis Salzwedel (SAW)	2,294	36	52.68,11.23
D2	Anhalt-Bitterfeld (ABI)	1,454	108	51.77,12.07
D3	Börde (BK)	2,367	72	52.22,11.35
D4	Burgenland (BLK)	1,414	125	51.15,11.88
D5	Harz (HZ)	2,105	100	51.82,10.96
D6	Jerichower Land (JL)	1,577	57	52.26,12.03
D7	Mansfeld-Südharz (MSH)	1,449	91	51.54,11.36
D8	Saalekreis (SK)	1,434	128	51.43,11.87
D9	Salzlandkreis (SLK)	1,427	130	51.85,11.64
D10	Stendal (SDL)	2,423	45	52.70,11.84
D11	Wittenberg (WB)	1,930	64	51.82,12.70
D12	Dessau-Roßlau (DE)	245	322	51.86,12.24
D13	Halle (Saale) (HAL)	135	1763	51.48,11.97
D14	Magdeburg (MD)	201	1175	52.13,11.62

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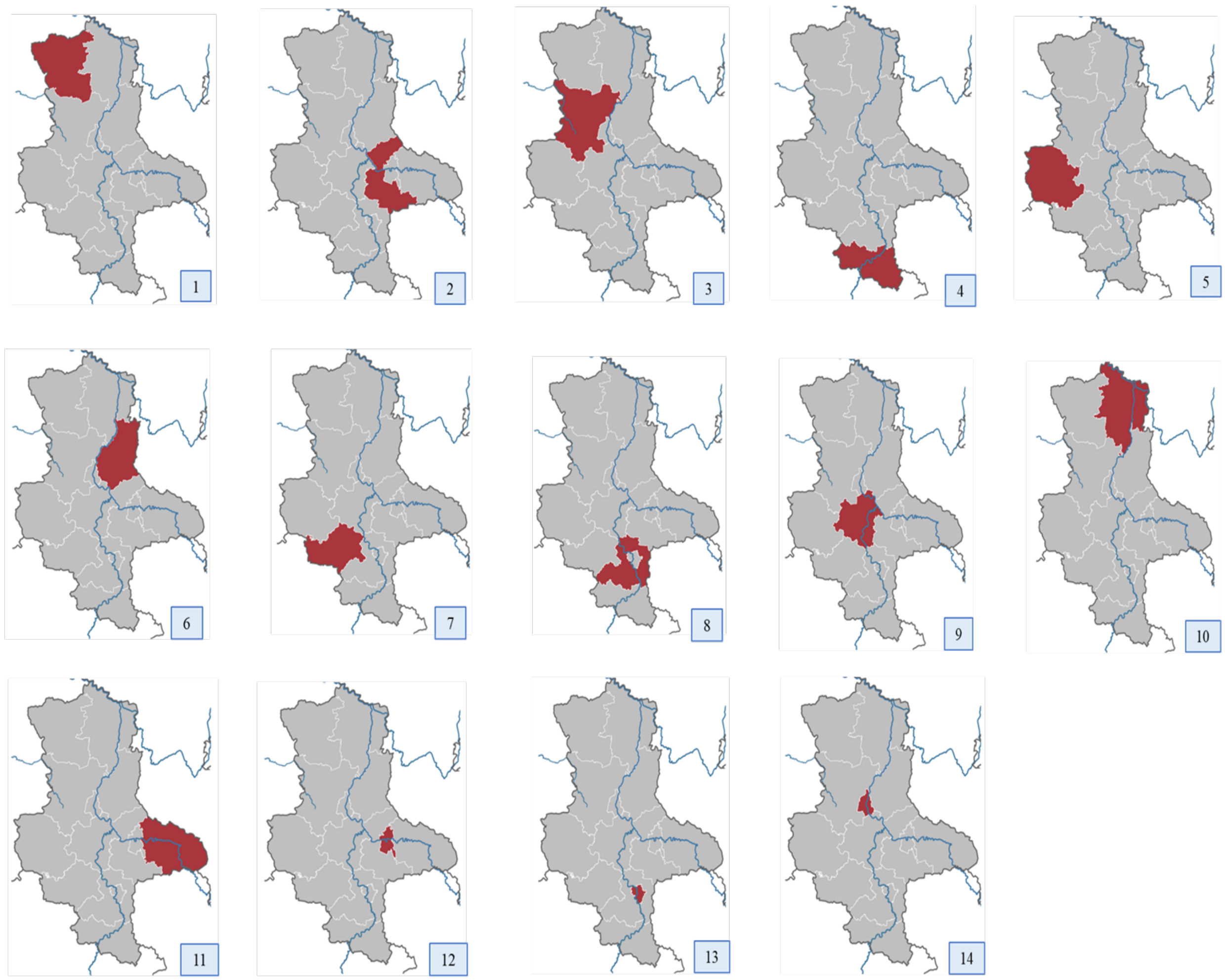

Figure 3. Locational maps of each decision-making unit for the case study

4.2 Input and Output Criteria

We next discuss the input and output criteria assessment for the solar energy plant location in the GHSC. In particular, the criteria list is collected from the literature and is based on the geographic, climate, and sun-earth interaction as follows (i.e., the Regional Atlas for Germany, the National Centers for Environmental Information, the German Weather Service, and the Global Solar Atlas). That is, seven input criteria are based on the area, the average air temperature, the average rainfall amount, the average precipitation days, the average humidity, the average yearly sunshine hours, and the wind force. Additionally, three output criteria are the population density, the direct normal irradiation, and the specific photovoltaic power output, respectively. A detailed description of the criteria is presented below.

Input C1: Area (km2): In this study, the area of each locational alternative is collected. Depending on the type of solar technology, the residential solar may be found on rooftops and other large-scale solar projects will need a secured area for the installation. Locations for solar development may also overlap with croplands or grasslands that should be considered. There is also a growing alternative to using land for solar power generation called agrivoltaics, which combines agriculture and solar power on the same land. Thus, the area criterion is also one important factor in the analysis.

Input C2: Air temperature (°C): The air temperature criterion also affects the solar system performance. Studies suggest that an increase in the temperature will potentially reduce the amount of energy a solar panel produces due to increased resistance. That is, high temperature will tend to affect the slow speed of the electrical current leading to reduced power generation.

Input C3: Rainfall precipitation amount (mm.): The average rainfall precipitation amount is used in this study as one of the climate-related criteria that affect the location problem for solar plants. Generally, the higher the rainfall precipitation, the lower the solar system efficiency. That is, the rainfall amount not only reduces the performance of the solar panels by reducing the reflection of sunlight but also can accumulate on the surface of the solar panels, reducing energy production.

Input C4: Rainfall days (day): The average rainfall days per month are used in this study. Solar panels in general can operate on a rainy day, in which the panel can generate power even during rainy weather. However, studies suggest that solar system efficiency may be reduced. Additionally, the performance of the system can also be considerably impacted for areas with particularly extreme rainfall. Additionally, it can also be expected that there will not be as much sunlight available to power the solar panel on rainfall days.

Input C5: Humidity (%): The average humidity criterion is also used in this study as one of the criteria affecting the performance of solar energy. In general, the higher the humidity, the lower the energy can be absorbed by solar cells. Existing studies also suggest that humidity not only will affect the efficiency of the solar cells but can also decrease the efficiency by 10-20% of the total power output produced.

Input C6: Sunshine hours: Solar panels are found to be most efficient during direct sunlight and will generate less electricity during cloudy conditions. In addition, peak sun hours are typically used to measure the sunlight intensity, which is key for solar power. Thus, the average sunshine hours per annum for each district and city are used as one of the criteria that affect solar plant location.

Input C7: Wind force (Beaufort Wind Scale): Wind force can encourage evaporation and keep solar panels dry. Thus, a windy climate can support an increase in energy production. Studies also suggest that wind can increase the output of solar panels by up to 43% as the cooling effect of the wind on solar panels can counteract the negative impact of solar panels overheating on warm sunny days.

Output C1: Population density (People/km2): The population density is computed from the population number and the total area of each locational alternative. Studies suggest that the higher the population density both per inhabitant and per household, the higher the energy consumption. Thus, higher demand for solar power can contribute to the cost-effectiveness of the installed solar plant. Thus, the population density criterion is used to reflect the potential demand for hydrogen energy in the HSC.

Output C2: Direct Normal Irradiance (kWh/m2): The Direct Normal Irradiance (DNI) is the amount of solar radiation received per unit area by a surface that is perpendicular to the rays of the sun. Studies also suggest that irradiance is a crucial factor that directly impacts the energy production potential and financial viability of a solar farm project. In addition, low solar irradiance can also have a significant negative impact on the power quality of the output of the solar system.

Output C3: Photovoltaic power output (kWh/kWp): The photovoltaic power output can be defined as the specific yield, which represents the amount of expected power generated per unit of the installed photovoltaic capacity over the long term, and is measured in kilowatt-hours per installed kilowatt-peak of the system capacity (kWh/kWp). Thus, the photovoltaic power is used as one of the important factors for the analysis in this study.

5. Results and Discussion

We next discuss results obtained from collecting data for all DMUs of all the input and output criteria. The collected data are based on the average computation from monthly data as well as based on the available data from the governmental units' websites. That is, data relevant to the population density and area are obtained from the governmental unit. Data for climate data relevant to the average rainfall precipitation amount and average rainfall days are collected from the National Centers for Environmental Information. In addition, data for the average air temperature, relative humidity, average wind force, and annual sunshine hours are collected from the German Weather Service website as presented in Figure 4. Finally, data relevant to the average direct normal irradiance and average photovoltaic power output are obtained from the global solar atlas, respectively. Table 2 presents collected data for all

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DMUs. Next, the data are analyzed using the proposed DEA model with the output-oriented approach (i.e., Model 2) and the input-oriented approach (i.e., Model 3). We note that Model 2 is the linear programming model for Model 1 as discussed earlier. The analyzed results are shown in Table 3.

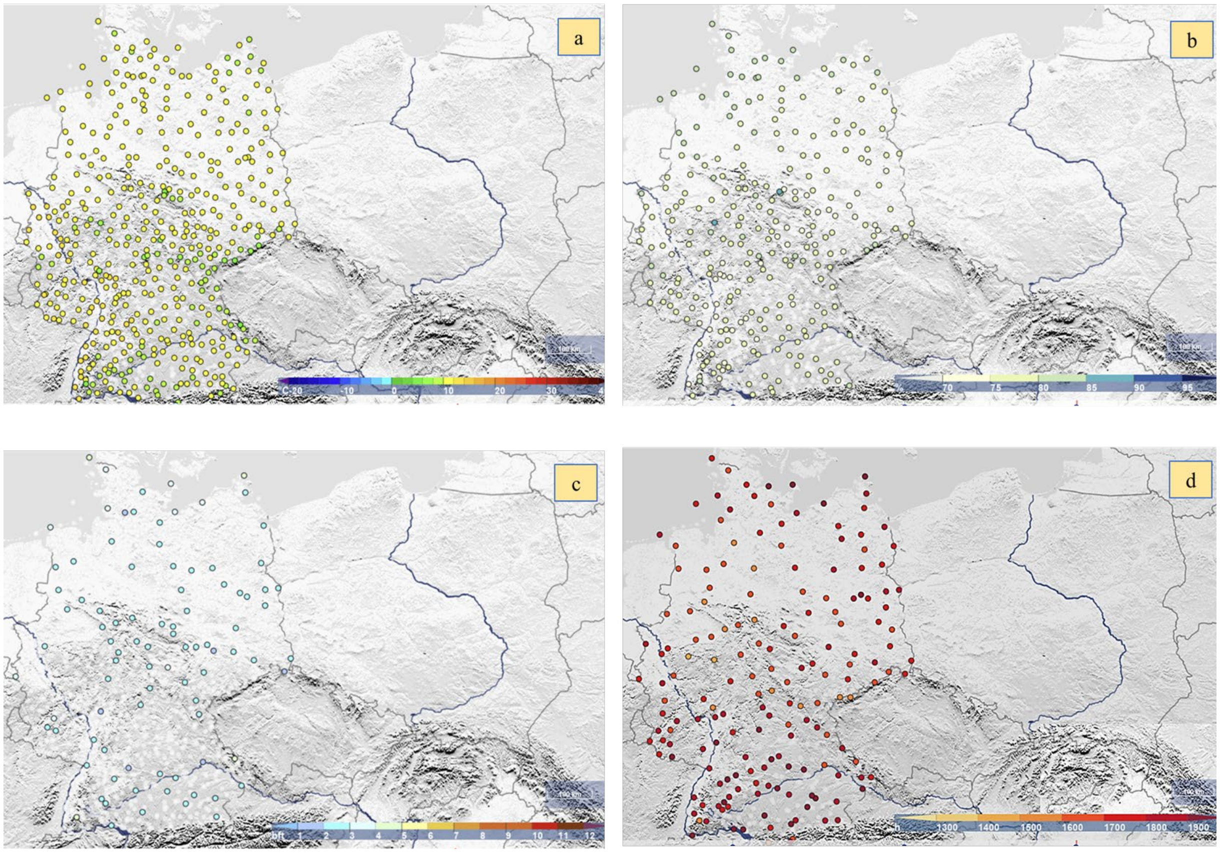

Figure 4. a) average air temperature, b) relative humidity, c) average wind force, and d) annual sunshine hours

Table 2. Collected data for all DMUs concerning all input and output criteria

DMUs	Input C1	Input C2	Input C3	Input C4	Input C5	Input C6	Input C7	Output C1	Output C2	Output C3
D1	2,294	10.10	45.19	8.00	76.92	1,654	2.18	36	963	1,064
D2	1,454	10.30	43.43	7.33	75.54	1,718	2.99	108	999	1,095
D3	2,367	9.60	41.64	7.58	78.13	1,682	2.16	72	1,002	1,096
D4	1,414	9.90	46.31	7.69	75.04	1,711	2.86	125	1,016	1,113
D5	2,105	7.40	38.48	6.08	74.39	1,618	2.41	100	922	1,038
D6	1,577	10.10	46.68	8.03	76.31	1,697	2.25	57	970	1,072
D7	1,449	8.70	41.41	7.17	76.19	1,667	2.78	91	982	1,089
D8	1,434	10.00	41.48	7.21	75.69	1,719	2.75	128	1,016	1,111
D9	1,427	10.10	41.52	7.21	75.68	1,714	2.13	130	1,013	1,106
D10	2,423	10.10	45.50	7.67	77.19	1,686	2.55	45	981	1,077
D11	1,930	10.20	46.37	7.97	74.73	1,724	2.48	64	996	1,091
D12	245	10.20	44.47	7.75	75.54	1,715	2.54	322	987	1,084
D13	135	10.30	40.03	6.83	73.96	1,731	2.44	1,763	998	1,091
D14	201	10.10	41.72	7.17	75.20	1,721	2.15	1,175	994	1,089

Table 3. DEA results for the case study

DMUs	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
Model 2	0.987	0.986	1	1	1	0.976	1	1	1	0.980	0.990	0.998	1	1
Model 3	1	0.991	1	1	1	0.988	1	1	1	0.989	0.995	1	1	1

As presented in Table 3, the efficient locational DMUs for both Models 2 and 3 are found to be D3 (i.e., Börde (BK)), D4 (i.e., Burgenland (BLK)), D5 (i.e., Harz (HZ)), D7 (i.e., Mansfeld-Südharz (MSH)), D8 (i.e., Saalekreis (SK)), D9 (i.e., Salzlandkreis (SLK)), D13 (i.e., Halle (Saale) (HAL)), and D14 (i.e., Magdeburg (MD)), respectively. That is, about 57% of all the evaluated DMUs for the state of Saxony-Anhalt in the case study are found to be relatively efficient and can serve as a benchmarking list when compared with the rest of other alternatives. It is also important to note that different models under evaluation depend also on the assumption of a return to scales (i.e., CRS vs. VRS assumptions). Additionally, it is worth emphasizing that the outcomes of this study also depend on the list of selection criteria under evaluation.

6. Conclusion

The success of the hydrogen economy depends on many factors and challenges regarding the economy assessment, technical development, sustainability evaluation, and performance evaluation for the key operations in the hydrogen supply chain. In this study, our focus is on the evaluation of the upstream process of the green hydrogen supply chain, in which the source of renewable energy is used rather than other non-renewable sources of energy. That is, the focus on solar energy is under investigation. In this study, we highlight the application of the DEA technique for evaluating potential locations for solar energy plants under multiple criteria using a case study in Germany. Our analyzed results can be strategically used to enhance not only a geographic-based case study but also provide analysis guidelines for policymakers and practitioners interested in GHSC. We note also that this is the first phase of our ongoing studies to compare and contrast policies between Germany and Thailand case studies in the GSHC framework and to model the GHSC network involving the upstream, the midstream, and the downstream operations.

Future research directions are suggested for three folds. That is, the first direction is to use the outcome from this study as input to the development of a model for analyzing hydrogen networks involving the upstream, the midstream, and the downstream operations, which is an ongoing research framework. The second direction is to verify and validate the results from this study with existing plans of the governmental units related to solar energy plan. Furthermore, the third direction for future research is to enhance the reliability of this study by also integrating the DEA technique with other MCDA tools as well as by comparing the findings with other studies and case studies.

References

Almutairi, K., Determining the appropriate location for renewable hydrogen development using multi-criteria decision-making approaches. *International Journal of Energy Research*, vol. 46(5), pp.5876-5895, 2022.

Azadnia, A.H., McDaid, C., Andwari, A.M. and Hosseini, S.E., Green hydrogen supply chain risk analysis: A European hard-to-abate sectors perspective. *Renewable and Sustainable Energy Reviews*, vol. 182, p.113371, 2023.

German Weather Service, Available: https://www.dwd.de/EN/Home/home_node.html, March 2024

Global renewable energy market size 2021-2030. Available: https://www.statista.com/statistics/1094309/renewable-energy-market-size-global/, March 2024.

Global Solar Atlas, Available: https://globalsolaratlas.info/map, March 2024

Hassan, Q., Algburi, S., Sameen, A.Z., Salman, H.M. and Jaszczur, M., Green hydrogen: A pathway to a sustainable energy future. *International Journal of Hydrogen Energy*, vol. 50, pp.310-333, 2024.

Hydrogen Council, 2022. Hydrogen insights 2022.

Jurasz, J., Canales, F.A., Kies, A., Guezgouz, M. and Beluco, A., A review on the complementarity of renewable energy sources: Concept, metrics, application and future research directions. *Solar Energy*, vol. 195, pp.703-724, 2020.

Kovač, A., Paranos, M. and Marciuš, D., Hydrogen in energy transition: A review. *International Journal of Hydrogen Energy*, vol. 46(16), pp.10016-10035, 2021.

Lee, S., Kim, H., Kim, B.I., Song, M., Lee, D. and Ryu, H., Site and capacity selection for on-site production facilities in a nationwide hydrogen supply chain deployment plan. *International Journal of Hydrogen Energy*, vol. 50, pp.968-987, 2024.

Lin, R.H., Ye, Z.Z. and Wu, B.D., A review of hydrogen station location models. *International Journal of Hydrogen Energy*, vol. 45(39), pp.20176-20183, 2020.

Liu, H. and Ma, J., A review of models and methods for hydrogen supply chain system planning. CSEE *Journal of Power and Energy Systems*, 2020.

Mostafaeipour, A., Rezayat, H. and Rezaei, M., A thorough investigation of solar-powered hydrogen potential and accurate location planning for big cities: A case study. *International Journal of Hydrogen Energy*, vol. 45(56), pp.31599-31611, 2020.

Nannar, S., Sindhuchao, S., Chaiyaphan, C. and Ransikarbum, K., Optimization of the sustainable food supply chain with integrative data envelopment analysis approach. *International Journal of Management Science and Engineering Management*, pp.1-16, 2024.

National Centers for Environmental Information, Available: https://www.ncei.noaa.gov/, March 2024

Oner, O. and Khalilpour, K., Evaluation of green hydrogen carriers: a multi-criteria decision analysis tool. *Renewable and Sustainable Energy Reviews*, vol. 168, p.112764, 2022.

Ransikarbum, K. and Kim, N., Data envelopment analysis-based multi-criteria decision making for part orientation selection in fused deposition modeling. In 2017 4th International Conference on Industrial Engineering and Applications (ICIEA), pp. 81-85, 2017.

Ransikarbum, K. and Pitakaso, R., Relative efficiency analysis of biomass agricultural plants using data envelopment analysis. *In E3S Web of Conferences* (Vol. 302, p. 01003). EDP Sciences, 2021.

Ransikarbum, K., & Kim, N., Importance of Multi-objective Evaluation in 3D Printing. Industrial Strategies and Solutions for 3D Printing: Applications and Optimization, John Wiley & Sons, 2024.

Ransikarbum, K., Chaiyaphan, C., Suksee, S. and Sinthuchao, S., Efficiency optimization for operational performance in green supply chain sourcing using data envelopment analysis: an empirical study. In International Conference on Computing and Information Technology, pp. 152-162, 2022. *Cham: Springer International Publishing*.

Ransikarbum, K., Chanthakhot, W., Glimm, T. and Janmontree, J., Evaluation of sourcing decision for hydrogen supply chain using an integrated multi-criteria decision analysis (MCDA) tool. *Resources*, vol. 12(4), p.48, 2023.

Rasul, M.G., Hazrat, M.A., Sattar, M.A., Jahirul, M.I. and Shearer, M.J., The future of hydrogen: Challenges on production, storage and applications. *Energy Conversion and Management*, vol. 272, p.116326, 2022.

Regional Atlas for Germany, Available: https://regionalatlas.statistikportal.de/, March 2024.

Ren, J.T., Chen, L., Wang, H.Y., Tian, W.W. and Yuan, Z.Y., Water electrolysis for hydrogen production: from hybrid systems to self-powered/catalyzed devices. *Energy & Environmental Science*, vol. 17(1), pp.49-113, 2024.

Riera, J.A., Lima, R.M. and Knio, O.M., A review of hydrogen production and supply chain modeling and optimization. International Journal of Hydrogen Energy.

Sgarbossa, F., Arena, S., Tang, O. and Peron, M., Renewable hydrogen supply chains: A planning matrix and an agenda for future research. *International Journal of Production Economics*, vol. 255, p.108674, 2023.

Sgarbossa, F., Arena, S., Tang, O. and Peron, M., Renewable hydrogen supply chains: A planning matrix and an agenda for future research. *International Journal of Production Economics*, vol. 255, p.108674, 2023.

Tsiropoulos, I., Nijs, W., Tarvydas, D. and Ruiz, P., Towards net-zero emissions in the EU energy system by 2050. *Insights from Scenarios in Line with the 2030*, 2020.

Wattanasaeng, N. and Ransikarbum, K., Sustainable planning and design for eco-industrial parks using integrated multi-objective optimization and fuzzy analytic hierarchy process. *Journal of Industrial and Production Engineering*, vol. 41(3), pp.256-275, 2024.

Xu, T., You, J., Li, H. and Shao, L., Energy efficiency evaluation based on data envelopment analysis: A literature review. *Energies*, Vol. 13(14), p.3548, 2020.

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