Hindawi
Science and Technology of Nuclear Installations
Volume 2022, Article ID 9297122, 9 pages
https://doi.org/10.1155/2022/9297122

Research Article

Machine Learning-Based Approach for Hydrogen Economic Evaluation of Small Modular Reactors

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Received 1 May 2021; Revised 2 June 2022; Accepted 18 August 2022; Published 1 September 2022

Academic Editor: Han Zhang

In this study, we evaluate hydrogen production costs using small modular reactors (SMRs). Furthermore, we employ a machine learning-based approach to predict important parameters that affect the hydrogen production cost. Additionally, we use a hydrogen economic evaluation program to calculate the hydrogen production cost when using the two types of SMRs: system-integrated modular advanced reactor (SMART) developed by the Korea Atomic Energy Research Institute (KAERI) and NuScale power module™ (NPM) developed by the NuScale Power, LLC. Different storage and transportation means were selected to find the cheapest option. Using SMART, storing hydrogen in compressed gas and transporting it through pipes (CG-Pipe) is the best option, with an estimated cost of USD 2.77/kg. Other options when using SMART include storing in compressed gas and transporting with a vehicle (CG-Vehicle), with an estimated cost of USD 3.27/kg; storing by liquefaction and transporting with a vehicle (L-Vehicle), with an estimated cost of USD 3.31/kg; and storing in metal hydrides and transporting with a vehicle (MH-Vehicle), with an estimated cost of USD 6.97/kg. Using NPM, CG-Pipe is the cheapest option to generate hydrogen, with an estimated cost of USD 2.95/kg. Other options include CG-Vehicle (USD 3.35/kg), L-Vehicle (USD 3.42/kg), and MH-Vehicle (USD 7.04/kg). Hydrogen production using SMART is cheaper than using NPM. However, the observed difference between the hydrogen production costs using the two reactors was insignificant. We conclude that the optimal hydrogen production cost ranges from USD 3.27/kg (CG-Vehicle) to USD 3.42 (L-Vehicle). This conclusion is because the common hydrogen transportation means is with a vehicle. From a machine learning-based approach, we determine the important parameters that affect hydrogen production costs. The most important parameter is the heat consumption (MWth/unit) at hydrogen generation plants, and other parameters include electricity rating and heat for hydrogen generation plants.

1. Introduction

One of the biggest challenges in revitalizing the hydrogen economy is to produce hydrogen in an eco-friendly way that does not emit greenhouse gases (GHGs). Currently, more than 95% of the global hydrogen production consists of extracted hydrogen produced by reforming natural gas. This natural gas is decomposed into steam at high temperature and pressure, and hydrogen is produced as a byproduct of the petrochemical process, but neither method is environmentally friendly. For each 1 kg of hydrogen produced from fossil fuels, about 10 kg of carbon dioxide is emitted. It is also argued that the hydrogen production based on renewable energy, such as solar and wind power, is still expensive, so it is necessary to produce hydrogen more cheaply and efficiently using nuclear power plants (NPPs). Currently, nuclear power is attracting attention as a method for mass-producing hydrogen in a safe manner. There are two main methods for producing hydrogen from NPPs. One of them is to extract hydrogen by decomposing water with electricity produced at an NPP. Renewable energy has limitations in electrolysis because the amount of electricity generated greatly varies according to the weather and season. If the intermittent solar and wind powers are supplemented by an NPP that can be operated 24 hours a day, green hydrogen can be continuously produced. The other method for producing hydrogen is high-temperature water electrolysis using the thermal energy of NPPs. This method electrolyzes steam produced in pressurized light-water reactors (LWRs). Using the high-temperature water electrolysis method, the hydrogen production efficiency can be increased and the production cost can be significantly reduced compared with the general low-temperature water electrolysis method. It has been well known that small modular reactors (SMRs) are key technologies for carbon neutrality in 2050. SMRs are characterized by reducing the size of a commercial NPP by 1/150 and integrating major equipment, such as nuclear reactor, steam generator, coolant pump, and pressurizer, into one container. The accident rate of SMRs is 1/1000 that of other existing NPPs. Due to its small size, the installation of SMRs is easy, and massive production is possible, so the construction cost is lower than that of other existing NPPs. SMRs can serve as a power supply source to compensate for the inconsistent energy supply by solar and wind powers due to the influence of sunlight and weather.

The increase in global economic growth has increased global energy demand. Global human development depends much on energy availability. Therefore, global economic growth must consider cost-effectiveness and should not jeopardize the environment. Hydrogen is regarded as clean energy; hence, it is a potential alternative to replace fossil fuels. Several studies are ongoing to find the best application of hydrogen as an alternative to fossil fuels with the main goal of solving the challenges of climate change by reducing the emission of GHGs [1]. Fossil fuels produce a large amount of energy consumed globally. However, fossil fuels are a source of carbon emission, which is a global challenge. Therefore, there is a need to find a balance between energy sources to meet the global energy demand, which would create little or no negative impact on the environment. Nuclear energy contributes to the energy mix, and it is a clean and reliable source of energy [2]. Other sources of energy that contribute significantly to the energy mix include natural gas and renewables. Although nuclear energy is considered clean and reliable, there is a safety concern, especially owing to recorded severe accidents, such as the Fukushima Daiichi NPP accident on March 11, 2011, in Japan.

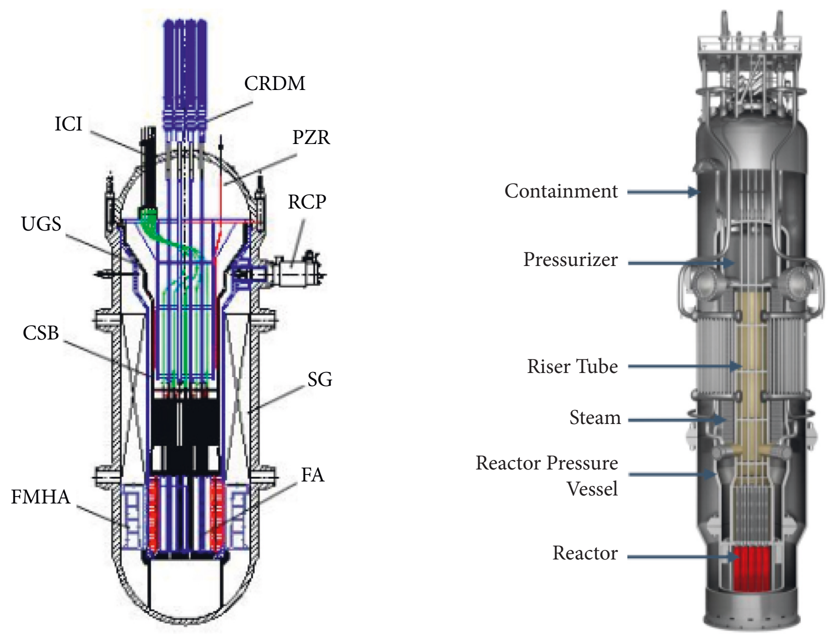
SMRs, among advanced technologies in NPPs, are designed to ensure safety and economic effectiveness with less impact on the environment. The design considers not only safety and cost but also climate change to maintain a clean environment by reducing the emission of GHGs [3]. SMRs have attracted interest from manufacturing companies and users, owing to their reduced total capital cost compared to large NPPs and ability to supply power to small-sized grid systems, especially in developing countries. SMRs are potential means of addressing the issues of microgrid, and land-based LWRs are the most developed technology [4]. The main differences between SMRs and large NPPs are their power output and modularity. SMRs have a small power output, typically less than 300 MWe/unit. In terms of modularity, SMR design modules can be produced in a factory, transported to a construction site, and installed to complete the power unit [5]. They play an important role in meeting global energy demand [6]. They can solve the energy demand of countries planning to expand their existing energy capacity, as well as countries planning to start the nuclear program, particularly those with restricted budgets and small electric grids [7]. SMRs can solve the electricity problems in some regions, which cannot capitalize on large NPPs. Such regions include people living in remote areas with no access to a grid, remote islands, and less populated areas with inadequate electricity supply [8]. SMRs are good candidates for future energy development, and currently, there are various concepts and designs of SMRs under development [9]. Compared with large NPPs, SMRs have various advantages, including improved safety, low investment cost, limited proliferation risk, reduced amount of nuclear wastes, a short construction time, long refueling time, and low maintenance cost. Additionally, they can be used in remote areas where there is no electricity. Also, they require a small area of site, and they can be located even in a populated area.

Other advantages of SMRs include a wide range of applications, for example, district heating [10], seawater desalination [11], and hydrogen generation [11]. Hydrogen generated from nuclear power has potential advantages over that from other sources, considering the hydrogen economy. This hydrogen does not require combusted fuel, and it generates lower GHGs and other pollutants. Hydrogen can be generated from nuclear power by low-temperature electrolysis, high-temperature electrolysis, thermochemical, and hybrid processes. Although SMRs are closely related to hydrogen production, only a few studies related to nuclear hydrogen economic evaluation have been conducted [12, 13]. In this study, we focus on SMRs for hydrogen generation, aiming at evaluating the economics of hydrogen production using SMRs by calculating the hydrogen production cost for system-integrated modular advanced reactor (SMART) and NuScale Power Module™ (NPM) using machine learning-based techniques. Machine learning methods have been widely used in various area of nuclear community such as multigroup neutron transport modeling [14], few-group constant neutron calculation [15], computational fluid dynamics (CFD) in complex accident scenarios [16, 17], fault detection and diagnosis in nuclear power plants [18, 19], and even nuclear forensics methodology for source discrimination of separated plutonium [20].

SMART was designed by the Korean Atomic Energy Research Institute (KAERI). SMART has a thermal power capacity of 330 MWth/unit. SMART was developed for the desalination of seawater. It is an integral type of reactor combining considerable proven technologies and advanced design features. The SMART design was approved by the Nuclear Safety and Security Commission, Republic of Korea, in 2012 [21]. SMART aims at achieving enhanced safety and better economics. SMART achieves enhanced safety by incorporating inherent safety-improving features and trusted passive safety systems. SMART realizes better economics by system simplification, component modularization, and construction time reduction. NPM is a new modular LWR developed to supply energy for generating electricity, district heating, desalination, and other applications. It is designed to generate electricity at 60 MWe/unit, and up to 12 power units can be combined. This scalable feature offers the advantages of carbon-free energy and economic benefits by

Table 1: Design parameters of SMART and NPM [22, 23].

	SMART	NPM
Reactor thermal output	330 MWth	200 MWth
Power plant output, net	90 MWe	60 MWe
Plant design life	60 years	60 years
Plant availability target	>95%	>95%
Reactor type	iPWR	iPWR
Primary coolant material	Light water	Light water
Refueling cycle	36 months	24 months
Thermodynamic cycle	Rankine	Rankine
Fuel material	UO_2	UO_2
Enrichment	<4.8%	<4.95%
Number of fuel assemblies	57	37
Nonelectric applications	Desalination, district heat, and hydrogen generation	Desalination, district heat, and hydrogen generation



CRDM : Control Rod Drive Mechanism
ICI : Incore Instrumentation
UGS : Upper Guide Structure
CSB : Core Support Barrel
FMHA : Flow Mixing Head Assembly
PZR : Pressurizer
RCP : Reactor Coolant Pump
SG : Steam Generator
FA : Fuel Assembly

(a) (b)

Figure 1: Structural diagram of SMART (a) and NPM (b) [15, 16].

reducing the financial commitments related to gigawatt-sized nuclear facilities [22]. Table 1 and Figure 1 show the main design parameters and general structural diagram of SMART and NPM, respectively.

2. Materials and Methods

In this study, we used two types of SMR: SMART developed by KAERI, Republic of Korea, and NPM developed by NuScale Power, LLC, USA. The hydrogen production cost was evaluated using the hydrogen economic evaluation program (HEEP). HEEP is computer software developed by the International Atomic Energy Agency (IAEA) to evaluate the techno-economic aspects of hydrogen production. It was developed to help IAEA member states meet their goal of hydrogen generation from nuclear energy to find a future role of hydrogen in the economic development of the country. The software consists of three modules: pre-processing, executing, and postprocessing modules. The preprocessing module provides the inputs, the executing

Table 2: Input parameters for hydrogen economic evaluation [22, 23].

Plant type	SMART	NPM
Financial parameters		
Discount rate (%)	3 or 5	3 or 5
Inflation rate (%)	1 or 3	1 or 3
Borrowing interest (%)	5 or 10	5 or 10
Tax rate (%)	5 or 10	5 or 10
Depreciation period (years)	20 or 40	20 or 40
Equity (%)	30 or 50 or 70	30 or 50 or 70
Debt (%)	30 or 50 or 70	30 or 50 or 70
NPP parameters		
Thermal rating (MWth/unit)	330	200
Heat for hydrogen plant (MWth/unit)	165 or 330	100 or 200
Electricity rating (MWe/unit)	0 or 165	0 or 100
Number of units	1 or 2	1 or 2
Initial fuel load (kg/unit)	15263	9250
Annual fuel feed (kg/unit)	1695.89	1541.6
Overnight capital cost (USD/unit)	2.52×10^8	1.53×10^8
Capital cost fraction for electricity-generating infrastructure	0 or 25	0 or 25
Fuel cost (USD/kg)	1958	1958
Operations and maintenance cost (% of capital cost)	2 or 4	2 or 4
Decommissioning cost (% of capital cost)	10 or 20	10 or 20
Hydrogen generation plant parameters		
Heat generation per unit (kg/year)	2.90×10^7	1.80×10^7
Heat consumption (MWth/unit)	165 or 330	100 or 200
Electricity required (MWe/unit)	0	0
Number of units	1	1
Overnight capital cost (USD/unit)	1.94×10^8	1.18×10^8
Energy usage cost (USD)	0	0
Operations and maintenance cost (% of capital cost)	2 or 4	2 or 4
Decommissioning cost (% of capital cost)	10 or 20	10 or 20
Hydrogen storage		
Storage capacity (kg)	5.56×10^5	3.45×10^5
Compressor cooling water (L/hr)	1.72×10^5	1.07×10^5
Electricity required (kWe)	7.58×10^5	4.70×10^5
Overnight capital cost (USD)	8.16×10^7	5.58×10^7
Compressor operating cost (USD)	3.98×10^6	2.47×10^6
Operations and maintenance cost (% of capital cost)	2 or 4	2 or 4
Decommissioning cost (% of capital cost)	10 or 20	10 or 20
Hydrogen transport		
Distance for transport (km)	200	200
Overnight capital cost (USD)	1.07×10^8	9.19×10^7
Electricity charges (USD)	2.77×10^6	1.72×10^6
Operations and maintenance cost (% of capital cost)	2 or 4	2 or 4
Decommissioning cost (% of capital cost)	10 or 20	10 or 20
Chronological details		
Construction years	3 or 5	3 or 5
Operating years	40 or 60	40 or 60

module computes the hydrogen production cost with the given inputs, and the postprocessing module displays the output from the executing module. The input parameters are grouped into two. The first group comprises the parameters common to all plants and facilities, including fiscal parameters and details associated with a period. The second group comprises facility-dependent parameters, including details relating to technical features and cost components [24]. HEEP calculates the levelized cost of hydrogen generation (LCHG) by considering various aspects of capital investments that affect the final estimated cost. The capital investment can be increased at a particular equity to debt ratio; that is, the project funding can be increased by equities, market borrowing, or a combination of both [25]. The LCHG using a nuclear source is calculated by HEEP using the following equation [26].

$$\mathrm{LCHG} = \frac{E_{npp}(t_o) + E_{H2GP}(t_0) + E_{H2T}(t_o)}{G_{H2}(t_o)}, \tag{1}$$

where $E_{npp}(t_o)$ is the current expenditure of NPP, $E_{H2GP}(t_0)$ is the current expenditure of the hydrogen plant, $E_{H2T}(t_o)$ is the current expenditure for hydrogen transport,

Table 3: Hydrogen production cost using SMART (USD/kg).

	Capital cost (debt)	Capital cost (equity)	Operation and maintenance refurbishment	Decommissioning cost	Fuel cost	Total cost
Hydrogen cost using CG-Pipe						
Nuclear power plant	0.29	0.37	0.34	0.08	0.16	1.24
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.09	0.12	0.14	—	—	0.36
Hydrogen transportation	0.15	0.09	0.1	—	—	0.33
Total of all facilities	0.75	0.87	0.86	0.12	0.16	2.77
Hydrogen cost using CG-Vehicle						
Nuclear power plant	0.29	0.37	0.34	0.08	0.16	1.24
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.09	0.12	0.14	—	—	0.36
Hydrogen transportation	0.03	0.02	0.78	—	—	0.83
Total of all facilities	0.64	0.8	1.55	0.12	0.16	3.27
Hydrogen cost using L-Vehicle						
Nuclear power plant	0.29	0.37	0.34	0.08	0.16	1.24
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.11	0.14	0.14	—	—	0.39
Hydrogen transportation	0.03	0.02	0.78	—	—	0.33
Total of all facilities	0.65	0.82	1.55	0.12	0.16	3.31
Hydrogen cost using MH-Vehicle						
Nuclear power plant	0.31	0.4	0.36	0.08	0.17	1.32
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	1.43	1.86	0.69	—	—	3.97
Hydrogen transportation	0.03	0.02	0.78	—	—	0.33
Total of all facilities	1.98	2.56	2.13	0.13	0.17	6.97

and $G_{H2}(t_o)$ is the gross amount of hydrogen generated. The current expenditure is calculated using the following equation:

$$E(t_0) = \sum_{N=N_i}^{N_f} \frac{C_{IN}}{(1+r)^{(N-N_O)}} + \sum_{N=N_i}^{N_f} \frac{C_{RN}}{(1+r)^{(N-N_O)}} + \sum_{N=N_i}^{N_f} \frac{C_{DN}}{(1+r)^{(N-N_O)}}, \tag{2}$$

where C_{IN} is the capital investment costs in year N, C_{RN} is the running cost in year N, C_{DN} is the decommissioning cost, and r is the discount rate.

The total cost of hydrogen generation can be calculated using various methods based on different available storage and transportation options in HEEP. The available storage options include compressed gas (CG), liquefaction (L), and metal hydrides. The available transportation options include pipes and vehicles. Thus, the total cost of hydrogen generation can be calculated using a combination of storage and transportation means. An example of such calculations is presented. Input parameters used in this study, including financial-, plant-, and hydrogen-related details, are summarized, as shown in Table 2.

3. Results and Discussion

Here, the total costs of hydrogen production estimated using HEEP for SMART and NPM are presented. The estimated costs comprise the costs of different facilities, including the NPP, hydrogen generation plant, and hydrogen storage and transportation means. For hydrogen storage, these three options are available: CG, L, and metal hydrides. For transportation, these two options are available: through pipes and vehicles. Table 3 lists the costs calculated using different options for SMART, and Table 4 lists those for NPM. The results presented in Tables 3 and 4 are plotted in Figure 2 to compare the hydrogen production cost using SMART and NPM, as well as between different storage-transportation combinations.

Hydrogen production cost using SMART is cheaper than using NPM, although the difference between the costs is insignificant. Considering the various storage-transportation combinations, for either type of reactor, the cheapest option is the combination of storage using compressed gas and transportation through a pipe (CG-Pipe). For this combination, the total cost of hydrogen production using SMART and NPM is USD 2.77/kg and USD 2.95/kg, respectively, whereas the hydrogen production costs by renewables, natural gas, and coal are USD 7.50/kg, USD 3.20/kg, and USD 2.20/kg, respectively [27]. The second cheapest option is the combination of storage using compressed gas and transportation by vehicle (CG-Vehicle). For this combination, the total cost of hydrogen production using SMART and NPM is USD 3.27/kg and USD 3.35/kg, respectively. The third cheapest option is the combination of storage by liquefaction and transportation by vehicle (L-Vehicle). For this combination, the total cost of hydrogen production using SMART and NPM is USD 3.11/kg and

Table 4: Hydrogen production cost using NPM (USD/kg).

	Capital cost (debt)	Capital cost (equity)	Operation and maintenance refurbishment	Decommissioning cost	Fuel cost	Total cost
Hydrogen cost using CG-Pipe						
Nuclear power plant	0.29	0.37	0.34	0.08	0.22	1.29
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.1	0.14	0.14	—	—	0.38
Hydrogen transportation	0.21	0.12	0.1	—	—	0.43
Total of all facilities	0.83	0.92	0.86	0.13	0.22	2.95
Hydrogen cost using CG-Vehicle						
Nuclear power plant	0.29	0.37	0.34	0.08	0.22	1.29
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.1	0.14	0.14	—	—	0.38
Hydrogen transportation	0.03	0.02	0.78	—	—	0.83
Total of all facilities	0.65	0.82	1.55	0.12	0.22	3.35
Hydrogen cost using L-Vehicle						
Nuclear power plant	0.29	0.37	0.34	0.08	0.22	1.29
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	0.13	0.17	0.14	—	—	0.44
Hydrogen transportation	0.03	0.02	0.78	—	—	0.83
Total of all facilities	0.67	0.85	1.55	0.12	0.22	3.42
Hydrogen cost using MH-Vehicle						
Nuclear power plant	0.31	0.4	0.36	0.08	0.23	1.38
Hydrogen generation plant	0.22	0.29	0.29	0.05	—	0.85
Hydrogen storage	1.43	1.86	0.69	—	—	3.98
Hydrogen transportation	0.03	0.02	0.78	—	—	0.83
Total of all facilities	1.99	2.57	2.13	0.13	0.23	7.04

USD 3.42/kg, respectively. The fourth cheapest option, which is the most expensive option, is the combination of storage using metal hydrides and transportation by vehicle (MH-Vehicle). For this combination, the total cost of hydrogen production using SMART and NPM is USD 6.97/kg and USD 7.04/kg, respectively.

The input parameters were also varied separately, and many observations that affect the hydrogen production costs were recorded. The dominant input parameters were predicted using a machine learning-based technique of classification and regression tree (CART®) models in Minitab statistical software. CART® classification is a robust decision tree tool that automatically searches for important relationships or patterns, uncovering hidden structures in the highly complex area of data mining, predictive modeling, and data preprocessing, without using parametric methods. Although decision trees are very popular algorithms, the methodology of CART® classification remains proprietary and distinguishes itself through its features and performance.

CART® regression is used to create a decision tree when there is a continuous response with many categorical or continuous predictors. Its results can identify important variables to see which predictors (input variables) are the most influential to the tree and even predict response values for new observations [28]. CART® regression tree results from a binary recursive partitioning of the training data sets. Any parent node from the training data set can split into two mutually exclusive child nodes in a finite node in a finite number of ways. For a continuous variable, X, and a value c, a split sends all records with values of $X \leq c$ to the left node and the remaining records to the right node. CART always uses the average of two adjacent values to calculate c. A continuous variable with N distinct values generates up to $N-1$ potential splits of the parent node. In an analysis, the actual number of potential splits is smaller when the minimum node size is greater than 1. For a categorical variable X with distinct values $\{c_1, c_2, c_3, \ldots, c_k\}$, a split is a subset of levels, which are sent to the left node. A categorical variable with k levels generates up to $2^{k-1}-1$ splits. For a potential split during the tree growing phase, the criteria for improvement are either least squares (LS) using equation (3). Minitab adds the split with the highest improvement to the tree. Minitab calculates improvements only from the training data when the analysis includes a model validation method [29].

$$\text{Improvement} = \text{SSE}_{\text{parent}} - \text{SSE}_{\text{left}} - \text{SSE}_{\text{right}}, \tag{3}$$

where $\text{SSE}_{\text{parent}} = \sum_{i\in\text{parent}}^{N_{\text{parent}}} (y_i - \overline{y}_p)^2$, $\text{SSE}_{\text{left}} = \sum_{i\in\text{left}}^{N_{\text{left}}} (y_i - \overline{y}_{\text{left}})^2$, and $\text{SSE}_{\text{right}} = \sum_{i\in\text{right}}^{N_{\text{right}}} (y_i - \overline{y}_{\text{right}})^2$.

The optimal tree is the tree with the least squared error or the tree with the least absolute deviation. The determination of the tree with the best value of the chosen criterion depends on the validation method. K-fold cross-validation is the default method in Minitab when the data have 5,000 cases or less. With this method, Minitab portions the data into K subsets. K-fold cross-validation tends to work well with data sets that relatively small compared with data sets that work well with a test data sets.

Any regression tree is a collection of splits. Each split provides improvement to the tree. Each split also includes

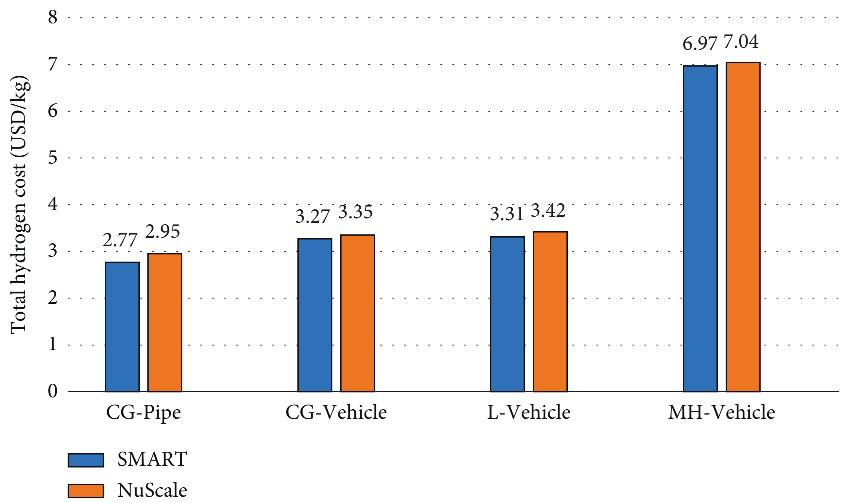


Figure 2: Comparison of hydrogen production cost using SMART and NPM.

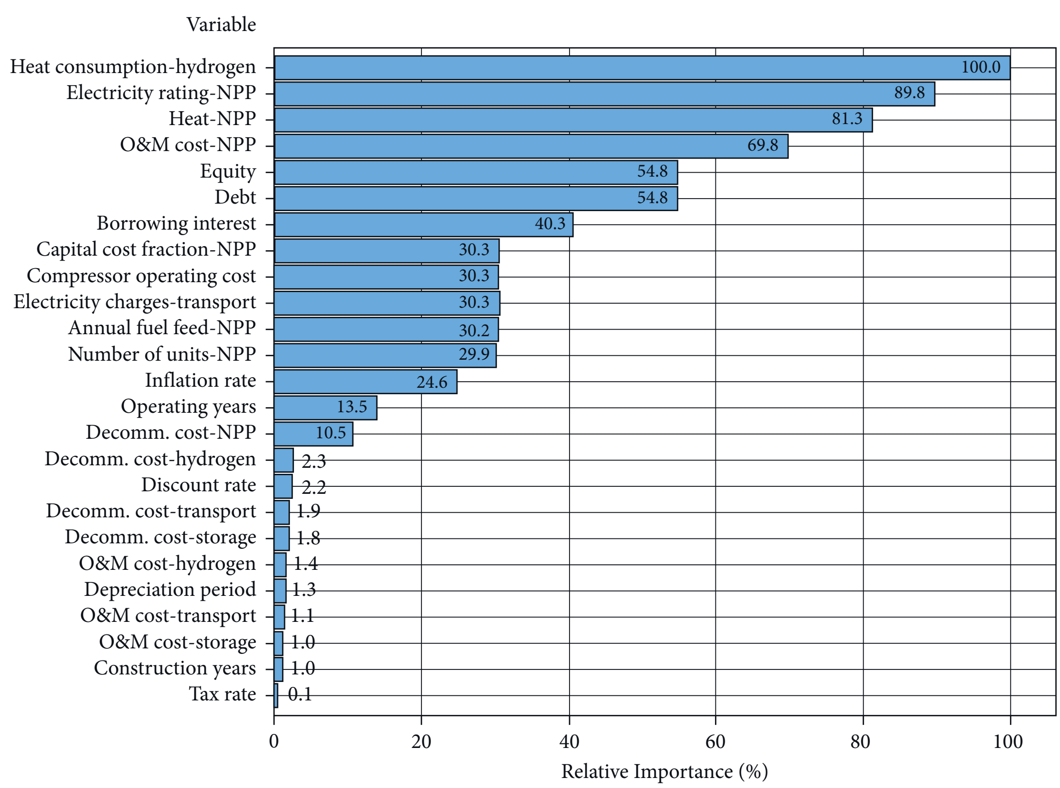


Figure 3: Relative importance of input parameters for nuclear hydrogen economic evaluation.

surrogate splits that also provide improvement to the tree. The importance of a variable is given by all of its improvements when the tree uses the variable to split a node or as a surrogate to split a node when another variable has a missing value. The following equation (4) gives the improvement at a single node.

$$\Delta I = I\left(t_{\text{parent node}}\right) - p_{\text{left}} I\left(t_{\text{left}}\right) - p_{\text{right}} I\left(t_{\text{right}}\right). \quad (4)$$

The values of $I(t)$, p_{left}, and p_{right} depend on the criterion for splitting the nodes. The relative variable importance graph plots the predictors in order of their effect on model improvement when splits are made on a predictor over the sequence of trees. The variable with the highest improvement score is set as the most important variable, and the other variables follow in order of importance. Relative importance is defined as the percent improvement with respect to the most important predictor, which has an importance of 100%. Relative importance is calculated by dividing each variable importance score by the largest importance score of the variables, then multiplied by 100%.

Among the 61 predictors as shown in Tables 2–4, 25 of them are found to be relatively important in terms of the hydrogen economic evaluation of SMRs. The first most important predictor is heat consumption at hydrogen generation plants, as shown in Figure 3. If the contribution of the first most important predictor, that is, heat consumption at hydrogen generation plants, is 100%, we can compare the other variables with the first most important predictor to determine their importance. The second most important variable is electricity rating at SMRs, which is about 90% as important as the first most important predictor. The third most important predictor is heat for hydrogen plants at SMRs, which is about 81% as important as the first most important predictor. The fourth most important predictor, which is the least most important predictor, is operations and maintenance cost at SMRs, which is about 70% as important as the first most important predictor.

4. Conclusion

Hydrogen production costs using SMRs, including SMART and NPM, were calculated using HEEP. It was found that hydrogen production cost using SMART is cheaper than that using NPM. Using SMART, the cheapest option is CG-Pipe, with an estimated cost of USD 2.77/kg. Other options using SMART include CG-Vehicle, L-Vehicle, and MH-Vehicle, with an estimated cost of USD 3.27/kg, USD 3.31/kg, and USD 6.97/kg, respectively. Using NPM, the cheapest combination is CG-Pipe, with an estimated cost of USD 2.95/kg. Other options using NPM include CG-Vehicle, L-Vehicle, and MH-Vehicle, with an estimated cost of USD 3.35/kg, USD 3.42/kg, and USD 7.04/kg, respectively. However, the observed difference in the hydrogen production costs between SMART and NPM is insignificant. From the results, the best means of hydrogen transportation are with a vehicle. Thus, we conclude that the optimal hydrogen production cost ranges from USD 3.27/kg (CG-Vehicle) to USD 3.42/kg (L-Vehicle). Using a machine learning-based technique, important parameters that affect the hydrogen production costs were predicted. We found that the most important parameter is the heat consumption (MWth/unit) at hydrogen generation plants, and the next important parameters include the electricity rating and heat for hydrogen plants at SMRs, in that order.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This research was supported by the Nuclear Safety Research Program through the Korea Foundation of Nuclear Safety (KoFONS) using the financial resource granted by the Nuclear Safety and Security Commission (NSSC) of the Republic of Korea (No. 1805018). This research was also supported by the 2022 Research Fund of the KEPCO International Nuclear Graduate School (KINGS), the Republic of Korea.

References

[1] International Atomic Energy Agency, *Hydrogen Production Using Nuclear Energy*, IAEA, Vienna, Austria, 2013.

[2] MIT Energy Initiative, *The future of Nuclear Energy in a Carbon-Constrained World*, Massachusetts Institute of Technology, Cambridge, MA, USA, 2018.

[3] M. Ruth, D. Cutler, F. Flores-Espino et al., *The Economic Potential of Two Nuclear-Renewable Hybrid Energy Systems*, The Joint Institute for Strategic Energy Analysis, Golden, CO, USA, 2016.

[4] S. Hong and B. W. Brook, "Economic feasibility of energy supply by small modular nuclear reactors on small islands: case studies of jeju, tasmania and tenerife," *Energies*, vol. 11, no. 10, p. 2587, 2018.

[5] Nuclear Energy Agency, *Small Modular Reactors: Nuclear Energy Market Potential for Near-Term Deployment*, NEA, Paris, France, 2016.

[6] International Atomic Energy Agency, *Design Safety Considerations for Water Cooled Small Modular Reactors Incorporating Lessons Learned from the Fukushima Daiichi Accident*, IAEA, Vienna, Austria, 2016.

[7] International Atomic Energy Agency, *Considerations for Environmental Impact Assessment for Small Modular Reactors*, IAEA, Vienna, Austria, 2020.

[8] International Atomic Energy Agency, *Options to Enhance Proliferation Resistance of Innovative Small and Medium Sized Reactors*, IAEA, Vienna, Austria, 2014.

[9] International Atomic Energy Agency, "Innovative small and medium sized reactors: design features, safety approaches and R&D trends," in *Proceedings of the Technical Meeting*, IAEA, Vienna, Austria, June 2004.

[10] A. Teräsvirta, S. Syri, and P. Hiltunen, "Small nuclear reactor—Nordic district heating case study," *Energies*, vol. 13, no. 15, p. 3782, 2020.

[11] International Atomic Energy Agency, *Approaches for Assessing the Economic Competitiveness of Small and Medium Sized Reactors*, IAEA, Vienna, Austria, 2013.

[12] I. Khamis and U. D. Malshe, "HEEP: a new tool for the economic evaluation of hydrogen economy," *International Journal of Hydrogen Energy*, vol. 35, no. 16, pp. 8398–8406, 2010.

[13] R. S. El-Emam, H. Ozcan, and I. Dincer, "Comparative cost evaluation of nuclear hydrogen production methods with the hydrogen economy evaluation program (HEEP)," *International Journal of Hydrogen Energy*, vol. 40, no. 34, pp. 11168–11177, 2015.

[14] J. J. Berry, G. G. Gil-Delgado, and A. G. S. Osborne, "Classification of group structures for a multigroup collision probability model using machine learning," *Annals of Nuclear Energy*, vol. 160, Article ID 108367, 2021.

[15] K. Tan, Z. Liu, C. Wei, and M. Liu, "The Assembly homogeneous few-group constants generation method for PWR based on machine learning," *Annals of Nuclear Energy*, vol. 165, Article ID 108772, 2022.

[16] B. N. Hanna, N. T. Dinh, R. W. Youngblood, and I. A. Bolotnov, "Machine-learning based error prediction

approach for coarse-grid computational fluid dynamics (CG-CFD)," *Progress in Nuclear Energy*, vol. 118, Article ID 103140, 2020.

[17] M. Liu, L. Wang, and Y. Lee, "Diagnosis of break size and location in LOCA and SGTR accidents using support vector machines," *Progress in Nuclear Energy*, vol. 140, Article ID 103902, 2021.

[18] L. M. Elshenawy, M. A. Halawa, T. A. Mahmoud, H. A. Awad, and M. I. Abdo, "Unsupervised machine learning techniques for fault detection and diagnosis in nuclear power plants," *Progress in Nuclear Energy*, vol. 142, Article ID 103990, 2021.

[19] A. M. Mwaura and Y.-K. Liu, "Prediction of the loss of feed water fault signatures using machine learning techniques," *Science and Technology of Nuclear Installations*, vol. 2021, Article ID 5511735, 13 pages, 2021.

[20] E. D. Kitcher, J. M. Osborn, and S. S. Chirayath, "Characterization of plutonium for nuclear forensics using machine learning techniques," *Annals of Nuclear Energy*, vol. 170, Article ID 108987, 2022.

[21] International Atomic Energy Agency, *Guidance on Nuclear Energy Cogeneration*, IAEA, Vienna, Austria, 2019.

[22] NuScale Power LLC, *Status Report–NuScale SMR*, NuScale Power, LLC, Portland, OR, USA, 2020.

[23] Korea Atomic Energy Research Institute, *Status Report 77-System-Integrated Modular Advanced Reactor (SMART)*, KAERI, Daejeon, Republic of Korea, 2020.

[24] International Atomic Energy Agency, *Examining the Techno-economics of Nuclear Hydrogen Production and Benchmark Analysis of the IAEA HEEP Software*, IAEA, Vienna, Austria, 2018.

[25] R. S. El-Emam and I. Khamis, "International collaboration in the IAEA nuclear hydrogen production program for benchmarking of HEEP," *International Journal of Hydrogen Energy*, vol. 42, no. 6, pp. 3566–3571, 2017.

[26] A. Y. Prawira, P. S. Kim, and M. S. Yim, "Techno-economic analysis of hydrogen production using nuclear power plant electricity generation in Korea," in *Proceedings of the Transactions of the Korean Nuclear Society Virtual Spring Meet*, Jeju-si, Republic of Korea, July 2020.

[27] International Energy Agency, *The Future of Hydrogen: Seizing Today's Opportunities*, IEA, Paris, France, 2019.

[28] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees*, Chapman & Hall/CRC, Boca Raton, FL, USA, 1984.

[29] Minitab LLC, *Predictive Analytics*, Minitab® Statistical Software, State College, PA, USA, 2021.