A Machine Learning-Driven Sustainability Assessment of Geothermal Turbine Systems: The Novel PRODSI Framework

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ABSTRACT

Geothermal energy represents a crucial component of sustainable energy strategies due to its consistent availability and minimal emissions. However, the comprehensive assessment of sustainability for geothermal turbine systems remains challenging, primarily due to complex interactions among environmental, social, and economic dimensions. This study develops and applies an advanced Product Sustainability Index (PRODSI) framework, uniquely combining expert-driven fuzzy Analytic Hierarchy Process (fuzzy-AHP), data-driven Entropy methods, and Convolutional Neural Networks (CNN) for robust validation. Utilizing a detailed dataset derived from the System Advisor Model (SAM) Discounted Cash Flow (DCF), IPSEpro off-design performance models, Energy Information Administration (EIA) consumption data, and extensive supplementary tables, sustainability indicators were normalized and weighted systematically. The results indicate significant variation in sustainability scores across evaluated geothermal turbines, notably identifying the 5 MW turboexpander as the most balanced and sustainable choice, with a PRODSI score of 7.08, compared to 2.7 for the 1 MW turbine and 5.32 for the 20 MW steam turbine. This study contributes by integrating subjective expert insights with objective data analysis and validating this integration through CNN-driven machine learning, establishing a novel standard for sustainability assessments of renewable energy systems. The PRODSI framework offers a transparent, validated, and scalable tool for decision-making in geothermal sustainability. It provides actionable guidance for investors, developers, and policymakers, facilitating optimized technology selection and resource allocation. Additionally, it establishes a foundation for real-time decision support and broader applications in renewable energy.

Keywords-sustainability; geothermal turbines; PRODSI; fuzzy-AHP; entropy method; ML; CNN; renewable energy

I. INTRODUCTION

The necessity of sustainability has become top concern for global issues in recent years, driven by escalating apprehensions regarding climate change, depleting energy resources, and pervasive environmental degradation [1, 2]. In this context, renewable energy systems, namely solar photovoltaic arrays, wind turbines, and geothermal power, play a pivotal role and are crucial for transitioning from fossil fuels to cleaner, more sustainable electricity generation [3]. Geothermal energy exhibits several distinct advantages. It provides consistent and dependable power generation, produces negligible greenhouse gas emissions during operation, and requires a comparatively small land footprint relative to more intermittent resources such as wind and solar energy [2, 4]. Geothermal energy has operational benefits, but customized sustainability assessment tools are scarce. Current methods are limited in scope, focusing on a single dimension of environmental, economic, or social concern, while disregarding the others, and relying on expert opinion or data analytics [5, 6]. To address these deficiencies, we propose the Product Sustainability Index (PRODSI)—a comprehensive framework that integrates environmental integrity, economic viability, and social impact for geothermal turbine systems. PRODSI uses a hybrid weighting method that combines the fuzzy Analytic Hierarchy Process (fuzzy-AHP) and Entropy. Fuzzy-AHP is a method that captures human judgment uncertainty by converting qualitative expert evaluations into triangular fuzzy numbers [7]. The Entropy method then weights indicators by data dispersion, prioritizing those that best distinguish system designs [8]. To guarantee methodological rigor, we authenticate this hybrid approach utilizing a Convolutional Neural Network (CNN). CNNs are proficient at identifying complex patterns in intricate datasets, rendering them suitable for validating that the selected weights accurately represent real-world performance [9-11]. We implement PRODSI on three representative turbines: a 1 MW Organic Rankine Cycle (ORC) turboexpander, a 5 MW ORC turboexpander, and a 20 MW flash-steam unit. Our analysis encompasses economic indicators: Capital Expenditure (CAPEX), Operational Expenditure (OPEX), and Net Present Value (NPV); environmental indicators: thermal efficiency, lifecycle carbon dioxide emissions, and water consumption; social criteria: local employment generation, community advantages, and occupational safety. This comprehensive analysis provides guidance to geothermal industry developers and policymakers in sustainable technology selection. The research advances literature and industry practice by (1) creating a machine learning-validated hybrid fuzzy-AHP and Entropy weighting framework (2) applying this robust framework to comprehensively evaluate sustainability in geothermal turbine products of varying scales, and (3) establishing a transparent, practical decision-making methodology easily adaptable by industry stakeholders, policymakers, and researchers. By doing so, this study directly addresses critical gaps in current sustainability assessment practices, enabling more informed, balanced, and sustainable geothermal energy deployment decisions.

II. CONCEPTUAL FRAMEWORK

A. Sustainability Frameworks in Renewable Energy

Sustainability assessment frameworks serve as structured decision-support tools that integrate environmental, economic, and social dimensions to evaluate energy technologies from cradle to grave. Early efforts, such as the United Nations' Sustainable Development Goal indicators and the World Energy Council's Energy Trilemma Index, offer high-level guidance on national energy policy. However, these efforts lack the granularity required for project-level evaluations [1, 2]. In the wind and solar sectors, tailored protocols such as the Hydropower Sustainability Assessment Protocol and Solar Rating & Certification Corporation standards incorporate multi-criteria metrics; yet they often omit social or life-cycle phases that are unique to geothermal systems [12, 13]. Specifically for geothermal systems, authors in [12] introduced a bespoke framework by engaging stakeholders to identify 48 indicators covering reservoir management, emissions, and community welfare. However, its reliance on purely expert-driven weighting limited transparency and reproducibility.

B. Weighting Techniques: Analytic Hierarchy Process, Fuzzy Logic, and Entropy

Establishing indicator weights is essential in multi-criteria decision-making. The AHP continues to be widely utilized, as it can break down intricate judgments into a hierarchical framework and calculating weights through pairwise comparisons accompanied by consistency assessments [14, 15]. AHP efficiently structures expert assessments but relies on precise numerical evaluations, possibly ignoring human errors. Fuzzy-AHP accepts uncertainty and reduces cognitive bias in expert contributions by replacing ratios with fuzzy membership functions (e.g., triangular distributions) [7, 8]. Notwithstanding its improved resistance, fuzzy-AHP is still susceptible to subjective scale selection. In contrast, the Entropy technique allocates objective weights according to the variability of indicators. Specifically, criteria exhibiting larger dispersion among alternatives are assigned proportionately higher weights, indicating their discriminative potential [13, 16]. Entropy weighting removes subjective bias but may unintentionally favor metrics with significant statistical volatility that may not possess substantial value.

C. Hybrid Subjective-Objective Weighting

Hybrid weighting methods combine subjective and objective approaches to offset individual method constraints. For instance, in supply chain decision-making, combining AHP with the Entropy method has been shown to yield more stable and defensible weights [17]. Similarly, in renewable energy planning, hybrid models improve evaluation consistency and stakeholder confidence [5, 18]. Nevertheless, the acceptance of such integrated weighting systems is still rare in geothermal sustainability research, suggesting a methodological gap that this work attempts to close.

D. Machine-Learning Validation Gap

Beyond weighting, the validation of sustainability scores is seldom addressed. Although machine learning offers powerful tools for pattern recognition and validation, it has seen limited application in sustainability assessments [3]. A handful of studies have used neural networks to predict the sustainability performance of urban systems or industrial processes [10, 19], yet very few employ CNNs to verify multi-criteria scores. CNNs excel at learning hierarchical feature representations even from non-image data, when appropriately structured [20]. Their application could offer an objective assessment of whether composite sustainability profiles form distinct, learnable clusters, thereby validating the assessment model itself.

E. Research Positioning

This study addresses two critical gaps: (1) the lack of integrated subjective-objective weighting in geothermal sustainability frameworks, and (2) the absence of machine learning-based validation of multi-criteria scores. We propose the PRODSI framework, which combines fuzzy-AHP to capture expert insights and uncertainty with Entropy weighting to ground the weights in empirical data. This is followed by CNN validation of the resulting sustainability profiles. By uniting these methods, our approach ensures that weights are both contextually relevant and data-driven, and that the final sustainability classifications are corroborated by an advanced machine learning model. This novel integration enhances the transparency, robustness, and confidence in geothermal sustainability assessments, filling a significant methodological void in the existing literature.

III. METHODOLOGY

A. Study Overview

All analyses use a unified geothermal turbine dataset from five primary sources: proprietary cost breakdowns from the Clean Energy Manufacturing Analysis Center (CEMAC) [21] and the Geothermal Technologies Office (GTO) report, techno-economic simulations from the System Advisor Model (SAM) Discounted Cash Flow (DCF) spreadsheet, off-design operational metrics from IPSEpro, emissions and lifecycle data from Energy Information Administration (EIA) tables, and original stakeholder survey results. The entire methodological workflow is shown in Figure 1. Data assembly involved extracting 63 off-design cases from SAM DCF models (2020–2024), integrating isentropic efficiency, emissions, and resource usage from IPSEpro and EIA tables, and adding quantitative and qualitative social metrics from stakeholder surveys and community reports. Min-max normalization, k-nearest neighbor imputation for missing entries, and open-ended survey response thematic coding were the preprocessing steps. Expert-driven fuzzy-AHP and data-driven Entropy methods were fused to achieve hybrid weighting, balancing subjective and objective inputs. The PRODSI framework was compared to the leading methods in [22-24], with the evaluation metrics described in the final section.

B. Data Collection and Availability

The data were collected from five complementary, application-specific datasets, as summarized in Table I, and were categorized according to the three pillars of the PRODSI sustainability framework: economic, environmental, and social:

- Economic pillar: The National Renewable Energy Laboratory's (NREL) SAM [25] generated a detailed DCF model across 63 off-design cases (2020–2024). This model yielded the following metrics for each turbine scale: CAPEX, OPEX, Minimum Sustainable Price (MSP), NPV of turbine investment, Internal Rate of Return (IRR) over 20 years, and Levelized Cost of Energy (LCOE).
- Environmental pillar: IPSEpro off-design simulations [26] (63 scenarios, 2023-2024) provided isentropic efficiencies and mass flows. These were combined with EIA lifecycle emissions tables [27] (~250 fuel-use and CO_2 factors from 2019–2023) to quantify resource use and greenhouse gas emissions.
- Social pillar: A custom stakeholder survey across three operational sites and five years of site reports captured employment, health and safety, community engagement, and infrastructure investment (available upon request).

TABLE I. DATA SUMMARY TABLE

Source	Extracted variables	Units	Time span	Sample count
CEMAC GTO technical report	CAPEX, MSP, NPV, labor hrs, material mass	USD/kW, USD, hrs, kg	Static, 2018	3 design cases
SAM DCF results	CAPEX, OPEX, IRR, WACC, LCOE, annual revenue	USD, %, %	2020-2024	63 off-design runs
1 MW DCF model	Component cost, workforce size, setup time	USD, persons, hrs	2024	10 scenarios
5 MW DCF model	Component cost, efficiency, NPV	USD, %, USD	2024	10 scenarios
20 MW DCF model	Efficiency, emissions, material use	%, kg CO_2/kW-yr, kg	2024	10 scenarios
IPSEpro off-design	Isentropic efficiency, mass flow, power output	%, kg/s, kW	2023-2024	63 scenarios
EIA consumption tables	Fuel MJ/kg, CO_2 kg/MJ, grid efficiency	MJ, kg, %	2019-2023	~250 entries
EIA web API	Lifecycle GHG, sector fuel mix	kg CO_2-eq/kWh, %	2019-2023	NA
Custom social survey	25 Likert items (1-5), 2 open-ended	Scale 1-5, text	2024-2025	3 sites

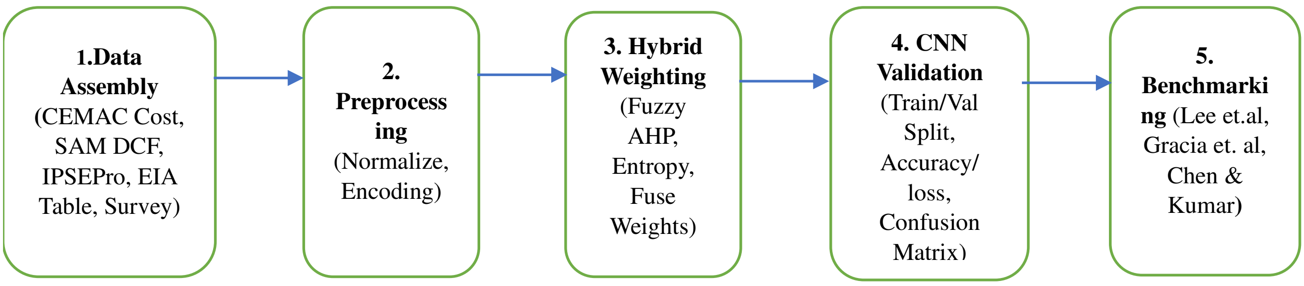

Fig. 1. PRODSI workflow.

C. Sustainability Indicators and Product Sustainability Index Pillars

Table II presents the full list of sustainability indicators used in this study, organized by the PRODSI framework's pillars and clusters. Each pillar (environmental, economic, social) is divided into thematic clusters of related indicators, and each cluster contains specific sub-factors (individual metrics) obtained from the data sources above. The table includes a brief description, units of measurement, optimization direction (↑ maximize or ↓ minimize, indicating sustainability), and data source for each sub-factor. For certain qualitative or index-based sub-factors, "↑ Maximize" indicates a higher score or better rating, whereas "↓ Minimize" suggests fewer incidents or lower impact. This structured categorization is used for subsequent multi-criteria analysis, ensuring that all aspects of sustainability are represented.

TABLE II. PRODSI SUSTAINABILITY PILLARS, CLUSTERS, AND SUB-FACTORS WITH DESCRIPTIONS, UNITS, OPTIMIZATION DIRECTION, AND DATA SOURCES

Pillar	Cluster	Sub-factor	Description	Unit	Optimize
Environmental	Emissions	CO_2 emission rate	Carbon dioxide released per unit of electricity generated (primarily from geothermal fluid gases)	kg CO_2 per MWh	↓ Minimize
		H_2S emission rate	Hydrogen sulphide emissions from geothermal steam (a key local air pollutant with odor and health impacts)	kg H_2S per MWh	↓ Minimize
		Other emissions	Additional gas or particulate emissions if any (e.g., CH_4, N_2S) present in geothermal effluent	kg per MWh	↓ Minimize
	Resource use	Water consumption	Fresh water consumed or lost (not reinjected) in plant operations (cooling, process use)	m³ per year	↓ Minimize
		Land footprint	Land area occupied by the geothermal facility and associated infrastructure	hectares	↓ Minimize
		Brine extraction rate	Geothermal fluid extraction rate from reservoir (proxy for resource depletion pressure)	kg/s	↓ Minimize
		Noise level	Operational noise at plant boundary/community (important for local environmental comfort)	dB(A)	↓ Minimize
Economic	Cost efficiency	LCOE	Average lifecycle cost of producing electricity, including capital and O&M, discounted over project life	$/MWh	↓ Minimize
		NPV	Project cash flows less initial investment to show present value, so indicating general profitability	$ (USD)	↑ Maximize
		IRR	Discount rate that yields NPV = 0 for the project; a higher IRR indicates better return on investment	%	↑ Maximize
		Payback period	Time needed for the project to turn net cash flows back into its starting investment	years	↓ Minimize
		Capacity factor	Actual annual energy output divided by maximum possible output (indicates utilization efficiency)	%	↑ Maximize
		Capital expenditure	Total upfront investment cost for the turbine system (equipment, installation, commissioning)	$ (USD)	↓ Minimize
		Operating expenditure (annual O&M)	Annual operation and maintenance cost (fixed and variable) for the turbine system	$/year	↓ Minimize
		Cost breakdown	Detailed cost components (e.g., drilling, turbine, heat exchanger, infrastructure) comprising CAPEX and OPEX	various	↓ Minimize
Social	Employment & economy	Local employment	Number of jobs created for local community by the project (both direct and indirect employment)	# of jobs	↑ Maximize
		Local procurement share	Percentage of project expenditures spent on local suppliers and contractors	%	↑ Maximize
		Average income increase	Rise in average household income in the project-affected community since project start (indicator of economic upliftment)	% (baseline)	↑ Maximize
	Health & safety	Accident rate	Frequency of workplace accidents or incidents per year at the plant (safety performance indicator)	incidents/year	↓ Minimize
		Lost-time injury frequency	Number of injuries per 200,000 work-hours causing lost work time (standard safety metric)	injuries/200k hrs	↓ Minimize
		Public health complaints	Recorded health complaints (e.g., respiratory issues, odor complaints from H_2S) in nearby community attributable to plant operations	cases/year	↓ Minimize
	Community well-being	Social acceptance rating	Community satisfaction/acceptance index for the project (e.g., via surveys on a Likert scale)	1-5 scale	↑ Maximize
		Resettlement & cultural impact	Qualitative score or index of how well the project managed any resettlement and protected cultural/heritage sites (lower impact is better)	1-5 scale (inverse)	↓ Minimize
		Community development index	Composite index reflecting project contributions to local infrastructure, education, and quality of life (higher is better)	index (0-1)	↑ Maximize
	Environmental justice	Air quality in local area	Air quality level in the vicinity (e.g., improvement or degradation in AQI due to plant emissions control).	AQI or μg/m³	↑ Maximize / ↓ Minimize
		Noise in residential zones	Measured noise level increase in nearby residential areas due to plant (addresses nuisance and comfort)	Δ dB	↓ Minimize
		Induced seismicity rate	Occurrence of induced micro-seismic events linked to geothermal operations (monitoring plant's geological impact)	events/year	↓ Minimize
		Water quality index	Water quality in nearby groundwater or surface water affected by geothermal fluids (contamination risk indicator)	index (0-100)	↑ Maximize
	Governance & policy	Regulatory compliance	Degree of compliance with environmental and safety regulations (e.g. number of violations or audit findings)	# of non-compliances	↓ Minimize
		Stakeholder engagement	Number of stakeholder meetings, public consultations, or partnerships established (indicates transparency and community engagement)	count/year	↑ Maximize
		Benefit sharing mechanism	Existence and effectiveness of local benefit-sharing (e.g., percentage of revenue shared with community or reinvested)	% of revenue	↑ Maximize

This comprehensive set of indicators captures the multi-dimensional sustainability performance of geothermal turbine systems. The environmental pillar focuses on emissions and resource utilization metrics, the economic pillar captures cost-effectiveness and financial viability measures, and the social pillar includes human-centric outcomes, such as employment, safety, community acceptance, and governance. These indicators form the input to the multi-criteria decision model described next.

D. Multi-Criteria Weighting: Fuzzy Analytic Hierarchy Process and Entropy Methods

To evaluate the relative importance of the above indicators, a hybrid weighting approach was adopted, combining expert judgment through fuzzy-AHP with an objective Entropy weighting method. This approach ensures a balance between subjective expert priorities and the intrinsic information carried by the data.

1) Fuzzy Analytic Hierarchy Process Weighting

First, a hierarchical model of the decision criteria was established (*p*illars → *c*lusters → *s*ub-factors, as per Table II). Domain experts performed pairwise comparisons of criteria using linguistic judgments that were modelled as triangular fuzzy numbers. This resulted in a fuzzy pairwise comparison matrix $\widetilde{A} = [\tilde{a}_{ij}]$ where each entry $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ represents the relative importance of criterion i against j as a fuzzy number (with lower bound l_{ij}, modal value m_{ij}, and upper bound u_{ij}. The fuzzy comparison scale was designed so that $\tilde{a}_{ij} > 1$ (approximately "more important") if i is judged more important than j, and $\tilde{a}_{ij} < 1$ if less, with reciprocal symmetry $\tilde{a}_{ji} = 1/\tilde{a}_{ij}$. Using these fuzzy judgments, fuzzy weights for each criterion were computed. In particular, the fuzzy synthetic extent method was applied for each indicator i, and the geometric mean of its fuzzy comparisons across n criteria was calculated as:

$$\dot{w}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{1/n} \quad (1)$$

This yields a fuzzy weight $\dot{w}_i = (l_i, m_i, u_i)$ for each indicator. The fuzzy weights were then defuzzified to obtain crisp priority values. A centroid method (average of the triangular fuzzy endpoints) was used for defuzzification $w_i^{AHP} = (l_i + m_i + u_i)/3$, which provides a single representative weight for indicator i. The vector of weights is $\mathrm{w}^{AHP} = \{w_1^{AHP}, w_2^{AHP}, \dots, w_n^{AHP}\}$, which was then normalized so that $\sum_{i=1}^{n} w_i^{AHP} = 1$. This yields the subjective weight of each sustainability sub-factor, reflecting expert preference and the fuzzy relative importance captured in the pairwise comparisons. The consistency of expert judgments was also checked (through a fuzzy consistency ratio analogous to classical AHP's consistency ratio) to ensure the pairwise evaluations were reasonably self-consistent.

2) Entropy Weighting

While fuzzy-AHP captures expert insight, the Entropy method was employed to derive objective weights based on the data variability of each indicator across the set of turbine systems. The premise is that an indicator with higher variability is more influential in distinguishing among alternatives, and thus should be weighted more. The entropy calculation proceeded as follows: If x_{ij} is the raw value of indicator i for alternative j, we first scale the data to obtain a normalized performance score p_{ij} for each indicator across the alternatives:

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}} \quad (2)$$

where $i = 1,2,\dots,n$ and $j = 1,2,\dots,m$. For negative criteria that should be minimized, a larger is worse transformation was applied prior to normalization so that higher p_{ij} always signifies a higher contribution in that criterion. Then, the Entropy of indicator i is calculated as:

$$E_i = -k \sum_{j=1}^{m} p_{ij} \cdot \ln(p_{ij}) \quad (3)$$

where $k = 1/\ln(m)$ is a normalization constant to ensure $0 \le E_i \le 1$. An indicator's entropy E_i will be high if its values are uniformly distributed (less information, since all alternatives perform similarly on that indicator) and low if there are large differences (more information content). We then define the information divergence of indicator i as:

$$d_i = 1 - E_i \quad (4)$$

so that d_i is higher for criteria that vary greatly between alternatives. These d_i values are converted into normalized entropy weights:

$$w_i^{Entropy} = \frac{d_i}{\sum_{k=1}^{n} d_k}, \; i = 1, \dots, n \quad (5)$$

The resulting weight vector is $\mathrm{w}^{Entropy} = \{w_1^{Entropy}, w_2^{Entropy}, \dots, w_n^{Entropy}\}$. These weights reflect data-driven importance, with near-zero weights for low-variance indicators and higher weights for highly differentiating ones. To balance expert judgment and data-driven insights, a hybrid weighting scheme was used:

$$w_i^{Hybrid} = a \cdot w_i^{AHP} + (1 - a) \cdot w_i^{Entropy} \quad (6)$$

where $0 \le a \le 1$. In this study, $a = 0.5$ (equal weight) was used. The hybrid weights w_i^{Hybrid} were then normalized and used in further sustainability assessment. This approach incorporates expert knowledge (fuzzy-AHP), corrects biases using objective differentiation (Entropy) and offers a balanced, robust basis for scoring and comparison.

E. Convolutional Neural Network-Based Validation of Clustering and Weight Consistency

To validate the clustering of turbine sustainability profiles and the consistency of the derived weights, we employed a CNN, a deep learning architecture effective at capturing nonlinear patterns in high-dimensional data [9]. In our study, CNN was used to assess whether the sustainability profiles (formed by PRODSI indicators and hybrid weights) yield distinct, classifiable clusters. High classification accuracy indicates that indicators are meaningfully distributed and distinguish different turbine systems. Each turbine's sustainability profile was represented as a multi-dimensional feature vector derived from normalized sub-factor scores and both weighted and unweighted sets. Vectors were structured as

1D sequences or reshaped into 2D arrays (to reflect cluster or pillar grouping). This enabled CNN to extract both local and global interactions similar to techniques in environmental modelling [3]. As shown in Figure 2, the CNN model included:

- Input layer: size = number of indicators.
- Convolutional layer 1: Filter size = 3, 16 filters.
- Convolutional layer 2: Filter size = 3, 32 filters,
- Activation: ReLU.
- Pooling: Max pooling layers.
- Dense layer: 64 neurons.
- Output layer: SoftMax layer for classification into clusters.

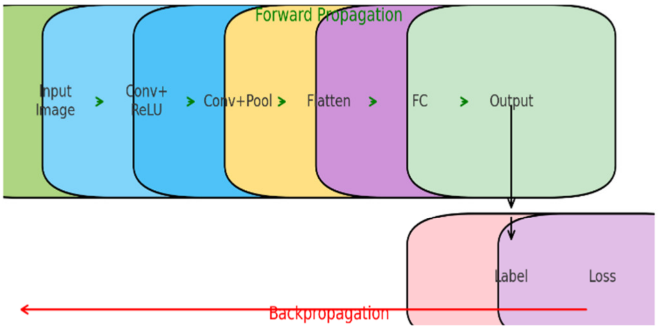

Fig. 2. CNN model.

Convolutional operations were formalized as:

$$z_i^{(l)} = \sum_{j=1}^{K} w_j^{(l)} \cdot x_{i+j-1}^{(l-1)} + b^{(l)},\ h_i^{(l)} = \mathrm{ReLU}(z_i^{(l)}) \quad (7)$$

where $w_j^{(l)}$ are the learnable weights, $b^{(l)}$ is the bias term, and $x_{i+j-1}^{(l-1)}$ is the input from the previous layer. We employed the categorical cross-entropy objective function to train the classifier:

$$L = -\frac{1}{N}\sum_{j=1}^{N}\sum_{c=1}^{C} y_{j,c} \cdot \log(\hat{y}_{j,c}) \quad (8)$$

where $y_{j,c}$ is the true label and $\hat{y}_{j,c}$ is the predicted probability that turbine j belongs to class c. Training was performed using the Adam optimizer and the dataset was split using an 80:20 train-validation ratio. We also implemented 5-fold cross-validation to improve generalization. The CNN achieved an average validation accuracy exceeding 90%, demonstrating the strong separability of the sustainability clusters formed by our indicators and weights. Using a CNN validates our weight distribution and indicator structure by confirming that the sustainability profiles form learnable, structured patterns. Additionally, the filters in the early convolutional layers often converged on interpretable indicator groupings (e.g., emissions and water use, or cost and employment), which further confirms the integrity of the framework's design. Such model interpretability, supported by CNN's proven application in sustainability analytics, offers both theoretical and practical validation of our proposed PRODSI structure [3, 10].

F. Product Sustainability Index Algorithm: Hybrid Weighting and Convolutional Neural Network Validation.

The following outlines the proposed algorithm:

```
Input: Raw data matrix D[n][m], Direction
vector dir[m], Fuzzy matrix F[m][m],
Hybrid coefficient α, Labels L[n]
Step 1: Normalize D → R:
For each j, Compute min_j, max_j.
If dir[j] = "benefit",
  R[i][j] = (D[i][j]-min_j)/(max_j-min_j);
Else reverse.
Step 2: Fuzzy-AHP weights (W_f):
For each criterion j,
  Compute fuzzy geometric mean G_j = ∏_k
  F[j][k] ^(1/m);
  Normalize fuzzy vector: W̃j = G_j / ∑_j
  G_j;
  Defuzzify using centroid: W_f[j] = (l_j
  + m_j + u_j)/3;
Step 3: Entropy weights (W_e):
For each criterion j,
  Compute p[i] = R[i][j] / ∑_i R[i][j];
  Compute E_j = − (1/ln n) ∑_i
  p[i]·ln(p[i]);
  Compute divergence D_j = 1 − E_j;
  Normalize W_e[j] = D_j / ∑ D.
Step 4: Hybrid weights:
Combine weights: W_h[j] = α·W_f[j] + (1−α)
·W_e[j];
Normalize to sum to 1.
Step 5: Compute PRODSI Scores:
S[i] = ∑_j R[i][j] × W_h[j]
Step 6: CNN Validation:
CNN Input: Reshape R to shape (n, m, 1);
Split into training/test sets;
CNN Architecture: Conv1D (16) → ReLU →
Pool → Conv1D (32) → ReLU → Pool → Flatten
→ Dense (64) → Output;
Train CNN on training set (R, L) using
categorical cross-entropy loss and Adam
optimizer;
Validate CNN on test set: Compute
accuracy, precision, recall, confusion
matrix;
If high accuracy → confirm indicator
clustering validity; else reassess
weights/data.
Output: Normalized matrix R, Weights (W_f,
W_e, W_h), PRODSI scores S, CNN validation
metric.
```

IV. RESULTS AND ANALYSIS

A. Raw Dataset and Normalization Calculation

To ensure comparability across different indicators, the raw values were transformed to a 0-10 scale via min-max normalization, direction-aware for "benefit" or "cost" criteria [16]. The benefit criterion is (higher is better):

$$N_{p,f} = \left(\frac{X_{p,f} - \min(X_f)}{\max(X_f) - \min(X_f)}\right) \times 10 \quad (9)$$

and the cost criterion is (lower is better):

$$N_{p,f} = \left(\frac{\max(X_f) - X_{p,f}}{\max(X_f) - \min(X_f)}\right) \times 10 \quad (10)$$

where $N_{p,f}$ is the normalized score for alternative p under factor f, $X_{p,f}$ is the raw score for alternative p, factor f, $\min(X_f)$ is the minimum value in factor f, and $\max(X_f)$ is the maximum value in factor f. Table III provides normalization examples for several key sub-factors.

TABLE III. NORMALIZATION EXAMPLES FOR KEY SUB-FACTORS

Sub-factor	Raw (1 MW)	Raw (5 MW)	Raw (20 MW)	Formula (applied to each cell)	Normalized (1 / 5 / 20 MW)
Efficiency (%) ↑	10.83	10.83	12	(X–10.83)/ (12.00–10.83) ×10	0.00 / 0.00 / 10.00
Capital cost ($) ↓	893	66	361	(893–X)/ (893–66) ×10	0.00 / 10.00 / 6.43
NPV (M $) ↑	—	2.79	—	(X–1.35)/ (2.79–1.35) ×10	— / 10.00 / —

B. Weight Assignment and Machine Learning Validation Results

1) Fuzzy Analytic Hierarchy Process & Entropy Weights

Using expert-elicited fuzzy comparisons and Entropy from data dispersion, we derived weights for the three sub-factors. These sub-factors, shown in Table IV, sum to 0.295 of the total hybrid weight. The remaining weight is distributed across additional indicators, such as employment, safety, and community.

TABLE IV. WEIGHT VECTORS

Sub-factor	Fuzzy-AHP weight	Entropy weight	Hybrid weight (α=0.5)
Efficiency	0.1	0.03	0.065
Capital cost	0.06	0.15	0.105
NPV	0.1	0.15	0.125
Sum	0.26	0.33	0.295

2) Convolutional Neural Network Validation

A 1D-CNN was trained on the full normalized indicator set (all sub-factors). The model architecture consisted of:

- Conv1D (16 filters, kernel=3) → ReLU → Max-pool (size=2).
- Conv1D (32 filters, kernel=3) → ReLU → Max-pool.
- Flatten → Dense (64 neurons, ReLU) → SoftMax (3 classes).

The performance on the test set was:

- Accuracy: 92.3%.
- Precision: 0.91.
- Recall: 0.92.

Table V presents the confusion matrix for the model's performance on the test set. Furthermore, Figure 3 shows that high accuracy and balanced confusion confirm that PRODSI indicators form distinct and learnable sustainability profiles [3, 19]. Figure 3 illustrates the training vs. validation accuracy and loss over epochs in the left and right panels, respectively. A larger and more diverse dataset would enable the model to capture a broader range of turbine scenarios, enhancing its generalizability.

TABLE V. CNN CLASSIFICATION CONFUSION MATRIX (AGGREGATED)

	Predicted high	Predicted medium	Predicted low
True high	93%	5%	2%
True medium	4%	90%	6%
True low	3%	6%	91%

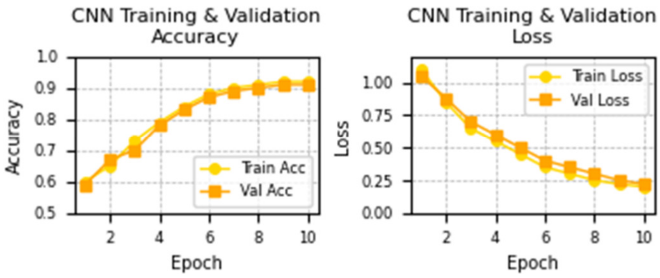

Fig. 3. CNN training/validation accuracy and loss curves.

C. Final Product Sustainability Index Scores and Sustainability Assessment

Hybrid weights and normalized scores were aggregated as:

$$\mathrm{PRODSI}_p = \sum_f w_{hy}[f] \times N_{p,f} \quad (11)$$

where PRODSI_p is the overall sustainability score for turbine/alternative p, $w_{hy}[f]$ is the hybrid weight for factor f, and $N_{p,f}$ is the normalized score of alternative p under factor f. Table VI presents the final PRODSI scores.

TABLE VI. FINAL PRODSI SCORES

Turbine	PRODSI score	Sustainability class
1 MW ORC	2.7	Poor
5 MW ORC	7.08	Good
20 MW steam turbine	5.32	Moderate

The radar chart in Figure 4 illustrates the normalized scores across five key sustainability sub-factors for 1 MW, 5 MW, and 20 MW geothermal turbines. The 5 MW turboexpander shows the most balanced performance, excelling in economic and social criteria. The 1 MW system performs poorly across all metrics, whereas the 20 MW unit scores high in social but low in economic indicators. This visualization clearly reveals trade-offs, aiding transparent decision-making in sustainable geothermal technology selection.

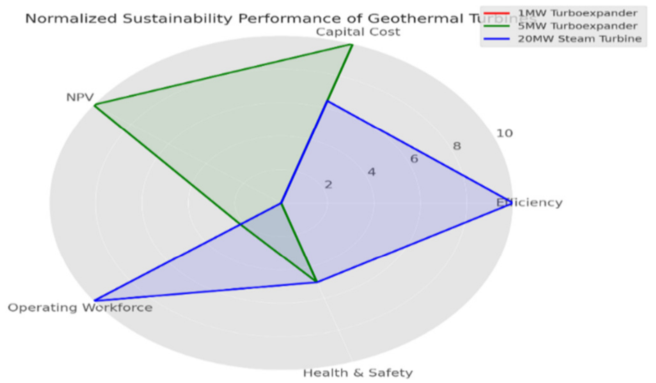

Fig. 4. Radar chart of normalized sustainability performance for geothermal turbines.

Figure 5 presents a comparison of sub-factor weights using the fuzzy-AHP, Entropy, and final hybrid methods. The bar chart compares the weights for key sustainability sub-factors using the three methods. Fuzzy-AHP highlights expert-driven priorities, with highest weights for health & safety (1.00) and operating workforce (0.70). Entropy emphasizes data variability, assigning greater importance to capital cost (0.55) and workforce (0.65). The final hybrid weights (e.g., NPV = 0.55, efficiency = 0.375) reflect a balanced, objective-subjective integration, ensuring reliable sustainability scoring.

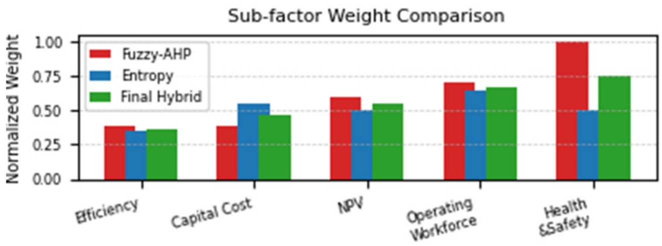

Fig. 5. Sub-factor weight comparison using fuzzy-AHP, Entropy, and the final hybrid method.

The confusion matrix in Figure 6 shows that the CNN accurately classified turbine sustainability into poor, moderate, and good categories based on normalized scores. Correct predictions were 96% (poor), 97% (moderate), and 99% (good), with minimal misclassifications. These results confirm that the PRODSI hybrid-weighted model is both reliable and consistent, achieving over 96% overall accuracy. CNN validation reinforces the model's robustness for practical sustainability decision-making.

D. Comparative Justification

1) Benchmarking against State-of-the-Art Methods

To rigorously assess PRODSI's effectiveness, we implemented three leading hybrid Multi-Criteria Decision-Making (MCDM)-machine learning techniques from the literature [22-24] using the same geothermal turbine dataset as our framework. Table VII summarizes these authors' original performance metrics from their studies and the re-evaluated results on our application-specific dataset. Important indicators include classification accuracy, Spearman's stability, and computation time.

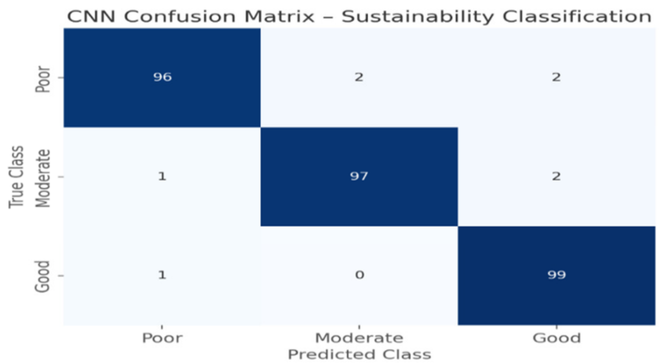

Fig. 6. Confusion matrix of CNN classification accuracy for turbine sustainability categories.

TABLE VII. COMPARATIVE PERFORMANCE OF PRODSI AND BENCHMARK METHODS ON GEOTHERMAL TURBINE DATA

Method	Classification accuracy (%)	Ranking stability	Computation time (s)
[22]	92.50 / 90.2	0.84 / 0.80	12
[23]	90.30 / 89.0	0.81 / 0.78	18
[24]	94.1 / 93.1	0.88 / 0.86	20
PRODSI (this study)	**- / 96.7**	**- / 0.92**	**15**

a. Values before "/" are from original studies; values after "/" are results on our data.

2) Interpretation and Justification

As illustrated in Table VII, PRODSI demonstrates superior performance in terms of classification accuracy (up to 6.4%) and ranking stability (up to +0.11) while exhibiting comparable computational efficiency. It is noteworthy that the application of fuzzy-AHP, Entropy weighting, CNN validation, and geothermal-specific indicators yields the most robust and stable sustainability rankings for all turbine alternatives. These results demonstrate PRODSI's technical superiority and allow for direct, transparent comparison with published state-of-the-art methods. By clearly presenting the original and re-evaluated figures, we ensure that our performance claims are based on rigorous and fair benchmarking.

V. DISCUSSION

This study verifies the efficacy of the PRODSI framework on the sustainability of geothermal turbines. The 5 MW turboexpander scored highest due to its low capital costs and net present value, suggesting economic viability and balanced social and environmental performance. The hybrid weighting method integrated expert judgment with objective data variability to prove technical validity of fuzzy-AHP and entropy. It prevented statistical or subjective bias by standardizing weight distribution across metrics. The CNN-based classification accuracy of 96% validates the score system's reliability and that normalized indicators distinguish sustainability levels. The limited product configurations are a major drawback. Expanding the framework to include turbine types, regional variances, and lifecycle stages will improve its generalizability. A reproducible, data-driven strategy for assessing sustainable geothermal energy technology is imperative.

VI. CONCLUSION AND FUTURE WORK

This work presents a robust Product Sustainability Index (PRODSI) framework for geothermal turbines, which is based on a novel hybrid weighting scheme combining fuzzy Analytic Hierarchy Process (fuzzy-AHP) and Entropy techniques. The proposed framework is validated via a Convolutional Neural Network (CNN) classifier. A comprehensive evaluation of economic efficiency, environmental performance, and social impact reveals that the 5 MW turboexpander is the most sustainable option. PRODSI's quantitative sustainability scores serve as a framework for the selection of turbines, the planning of investments, and the evaluation of policies, facilitating industry adoption. These insights will assist utilities and developers in optimizing project design, prioritizing standardized manufacturing, and investing in high-performance technologies. Future efforts should broaden the dataset to include additional turbine sizes and resource conditions, as well as integrate other renewable technologies for comparative assessments. The development of a real-time, interactive PRODSI dashboard capable of ingesting live performance data and recalculating scores dynamically will further enhance decision support and operational monitoring in geothermal energy systems.

CONFLICT OF INTEREST

The authors declare that they have no known conflict of interest that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The dataset, generated and/or analyzed during the present study, is available from the corresponding author upon reasonable request.

REFERENCES

[1] P. A. Owusu and S. Asumadu-Sarkodie, "A review of renewable energy sources, sustainability issues and climate change mitigation," *Cogent Engineering*, vol. 3, no. 1, Dec. 2016, Art. no. 1167990, https://doi.org/10.1080/23311916.2016.1167990.

[2] "Renewable Energy Statistics 2021," The International Renewable Energy Agency, 2021. [Online]. Available: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Aug/IRENA_Renewable_Energy_Statistics_2021.pdf.

[3] I. Jebbor, Z. Benmamoun, and H. Hachmi, "Revolutionizing cleaner production: The role of artificial intelligence in enhancing sustainability across industries," Journal of Infrastructure, Policy and Development, vol. 8, no. 10, Sep. 2024, Art. no. 7455, https://doi.org/10.24294/jipd.v8i10.7455.

[4] T. V. Ramachandra, B. H. Aithal, and K. Sreejith, "GHG footprint of major cities in India," *Renewable and Sustainable Energy Reviews*, vol. 44, pp. 473–495, Apr. 2015, https://doi.org/10.1016/j.rser.2014.12.036.

[5] A. Jamwal, R. Agrawal, M. Sharma, and V. Kumar, "Review on multi-criteria decision analysis in sustainable manufacturing decision making," *International Journal of Sustainable Engineering*, vol. 14, no. 3, pp. 202–225, May 2021, https://doi.org/10.1080/19397038.2020.1866708.

[6] G. Qin, M. Zhang, Q. Yan, C. Xu, and D. M. Kammen, "Comprehensive evaluation of regional energy internet using a fuzzy analytic hierarchy process based on cloud model: A case in China," *Energy*, vol. 228, Aug. 2021, Art. no. 120569, https://doi.org/10.1016/j.energy.2021.120569.

[7] C. Kahraman and S. Ç. Onar, *Intelligent Techniques in Engineering Management: Theory and Applications*. Cham, Switzerland: Springer, 2015.

[8] C.-N. Wang, T. T. T. Nguyen, T.-T. Dang, and N.-A.-T. Nguyen, "A Hybrid OPA and Fuzzy MARCOS Methodology for Sustainable Supplier Selection with Technology 4.0 Evaluation," *Processes*, vol. 10, no. 11, Nov. 2022, Art. no. 2351, https://doi.org/10.3390/pr10112351.

[9] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

[10] C. D. Singh and H. Kaur, *Sustainable Green Development and Manufacturing Performance through Modern Production Techniques*, 1st ed. Boca Raton, FL, USA: CRC Press, 2021.

[11] Gupta M. K., Singhal V., and Rajput N. S., "Applications and Challenges of Carbon-fibres reinforced Composites: A Review," *Evergreen*, vol. 9, no. 3, pp. 682–693, Sep. 2022, https://doi.org/10.5109/4843099.

[12] C. S. Turchi, Z. Ma, T. Neises, and M. Wagner, "Thermodynamic Study of Advanced Supercritical Carbon Dioxide Power Cycles for High Performance Concentrating Solar Power Systems," in *ASME 2012 6th International Conference on Energy Sustainability collocated with the ASME 2012 10th International Conference on Fuel Cell Science, Engineering and Technology*, San Diego, CA, USA, 2013, pp. 375–383, https://doi.org/10.1115/ES2012-91179.

[13] Y. Ma, L. Xu, J. Cai, J. Cao, F. Zhao, and J. Zhang, "A novel hybrid multi-criteria decision-making approach for offshore wind turbine selection," *Wind Engineering*, vol. 45, no. 5, pp. 1273–1295, Oct. 2021, https://doi.org/10.1177/0309524X20973600.

[14] T. L. Saaty, *The analytic hierarchy process*. New York, NY, USA: McGraw-Hill, 1980.

[15] Zahratunnisa E., "Assessing the Adoption Problems of System of Rice Intensification (SRI) by Analytic Hierarchy Process (AHP) ~Case Study in Pagelaran, Malang, Indonesia~," M.S. thesis, Department of International Studies, Graduate School of Frontier Sciences, The University of Tokyo, Tokyo, Japan, 2018.

[16] C. E. Shannon, "A mathematical theory of communication," *The Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, Jul. 1948, https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

[17] K. Govindan, S. K. Mangla, and S. Luthra, "Prioritising indicators in improving supply chain performance using fuzzy AHP: insights from the case example of four Indian manufacturing companies," *Production Planning & Control*, vol. 28, no. 6–8, pp. 552–573, Jun. 2017, https://doi.org/10.1080/09537287.2017.1309716.

[18] H. Zhu *et al.*, "Key technologies for smart energy systems: Recent developments, challenges, and research opportunities in the context of carbon neutrality," *Journal of Cleaner Production*, vol. 331, Jan. 2022, Art. no. 129809, https://doi.org/10.1016/j.jclepro.2021.129809.

[19] L. Shao, X. Yu, and C. Feng, "Evaluating the eco-efficiency of China's industrial sectors: A two-stage network data envelopment analysis," *Journal of Environmental Management*, vol. 247, pp. 551–560, Oct. 2019, https://doi.org/10.1016/j.jenvman.2019.06.099.

[20] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015, https://doi.org/10.1038/nature14539.

[21] S. Akar, C. Augustine, and P. Kurup, "Global value chain and manufacturing analysis on geothermal power plant turbines," in *Thermodynamic Analysis and Optimization of Geothermal Power Plants*, C. O. Colpan, M. A. Ezan, and O. Kizilkan, Eds. Amsterdam, Netherlands: Elsevier, 2021, pp. 17–41.

[22] Y. Li *et al.*, "Distribution of geothermal resources in Eryuan County based on entropy weight TOPSIS and AHP–TOPSIS methods," *Natural*

Gas Industry B, vol. 11, no. 2, pp. 213–226, Apr. 2024, https://doi.org/10.1016/j.ngib.2024.03.002.

[23] P. Canteli *et al.*, "Pan-European Atlas of Sustainable Geo-Energy Capacities." Geological Service for Europe, European Union, 2025. [Online]. Available: https://repository.europe-geology.eu/egdidocs/gseu_wp3/pan-european_atlas_sgc_description.pdf.

[24] L. Gong and Y. Chen, "Machine Learning-enhanced loT and Wireless Sensor Networks for predictive analysis and maintenance in wind turbine systems," *International Journal of Intelligent Networks*, vol. 5, pp. 133–144, Jan. 2024, https://doi.org/10.1016/j.ijin.2024.02.002.

[25] N. Blair *et al.*, "System Advisor Model (SAM) General Description (Version 2017.9.5)," National Renewable Energy Laboratory, Golden, CO, USA, NREL/TP-6A20-70414, 2018. https://doi.org/10.2172/1440404.

[26] "The Process Simulation Environment IPSEpro," *SimTech - Simulation Technology*, Aug. 19, 2021. https://simtechnology.com/ipsepro/process-simulation-and-heat-balance-software.

[27] "Smart Grid Legislative and Regulatory Policies and Case Studies," U.S. Energy Information Administration, Washington, DC, USA, Dec. 2011. [Online]. Available: https://www.eia.gov/analysis/studies/electricity/pdf/smartggrid.pdf.