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Article

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A Combined Ranking and Sensitivity Analysis of Power Generation Using Multi-Criteria Decision-Making and Monte-Carlo Simulation

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ABSTRACT

This research examined energy sources that can be employed in a region to assist policymakers in determining energy priorities. Three key components were analyzed in this research to rank these energy sources: Levelized Cost of Energy (LCOE), CO_2 emissions, and power density. A combination of multi-criteria decision-making (MCDM) methods, namely the Analytical Hierarchy Process (AHP)-Entropy-the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), was used to assess these criteria, which had not been previously applied to rank energy sources. Additionally, the Monte-Carlo method was utilized to detect changes in sensitivity throughout the rankings. Results of the study indicated that gas energy topped the list, followed by Solar Photovoltaic (PV)-crystalline, geothermal, wind, nuclear, Solar PV Commercial and Industrial (C&I), Solar Thermal Tower with Storage, and residential PV rooftop solar. Moreover, nuclear energy ranked the highest when looking at the sensitivity of parameters, while utility-scale Solar PV and wind energy ranked the next highest. Thus, this research can be used to increase objectivity in the assessment and selection of power generation technology to be implemented.

Keywords: Energy Ranking, CO_2 Emission, Levelized Cost of Energy, Power Density, Sensitivity Analysis, Multi-Criteria Decision-Making
JEL Classifications: Q01, Q48

1. INTRODUCTION

Developing countries must strategically position themselves to align with the green revolution's targets swiftly; otherwise, the green process will not effectively reduce global inequalities but may widen the gaps. As an illustrative example, Indonesia aims to achieve a 23% share of renewable energy in its energy mix by 2025 (National Energy Council (DEN), 2014). However, attaining this target poses significant challenges due to the dominance of coal business interests in its energy policies, limited understanding of existing local potential, and inadequate information on selecting compatible power generation technologies to support clean energy development. The urgent need to phase out coal and embrace renewable energy sources is apparent in a world constrained by carbon emissions. However, it is important to acknowledge that developing countries may require additional time to fully adopt and integrate new technologies that can replace the long-standing reliance on fossil fuels. One such example is the ASEAN region's photovoltaic (PV) market, which is still evolving into a stable and self-sustaining industry (Sreenath et al., 2022). Therefore, it becomes crucial to establish effective policies and support mechanisms within ASEAN countries to facilitate the transition to renewable energy sources. The developing nations, on their own, may struggle to fully capitalize on the benefits of transitioning energy systems, making immediate support from the international community imperative.

Furthermore, the successful transfer of green technology from developed to developing nations holds significant importance. However, it is essential to recognize that the impact of such technology deployment can vary based on the local context and how it is utilized. Technological advancements often bring positive and negative consequences, depending on factors such as the availability of resources, infrastructure capabilities, and socioeconomic conditions of the target region. Therefore, when transferring green technology, it is crucial to carefully assess and tailor the implementation strategies to suit the specific needs and challenges of the receiving developing nations. This approach will help maximize the positive impact of the technology while mitigating any potential negative consequences.

Data and information related to the performance of power plants from various types of technology have been widely published. These power plants tend to perform similarly in multiple places if the technology and environmental conditions are the same. Technology assessment and selection usually focus on only 1 (one) data variable, for example, economic or environmental aspects. It is necessary to consider several data variables to be more objective in choosing the right power generation technology, especially to produce a performance that accelerates the energy transition process. Furthermore, ranking the various technologies to be used can determine priorities and increase the effectiveness and efficiency of their utilization.

Renewable Energy (RE) has lower power densities than non-RE. As a result, RE systems often require more surface area to produce the same amount of power as non-RE systems (Smil, 2010) (van Zalk and Behrens, 2018). Power density is the quantity of power processed per unit volume of the unit area. While power density is measured in various ways, it is most commonly represented in watts per square meter (W/m^2) or square inch (W/in^2). Because modern engineering is driven by cost-efficiency, it is the key to generating more electricity in a smaller space while lowering prices, meaning more significant power density is better than less one. The National Renewable Energy Laboratory (NREL) in the United States uses power densities to estimate the energy generated by each recognised technology, considering system performance, topographic restrictions, and environmental and land-use constraints (Lopez et al., 2012). Examining the trade-off between land use and its social implications can help improve understanding of power densities. (Buceti, 2014) has researched the needs of land use related to power density, as shown in Table 1.

Like its power density, renewable power generation costs have fallen sharply over the past decade, but RE's Levelized Cost of Energy (LCOE) is still higher than fossil fuel (IRENA, 2020), as shown in Figure 1. Some efforts must be made to reduce RE's LCOE because a lower LCOE will make energy investment more attractive to investors (IRENA, 2020). LCOE is an economic statistic that compares the lifetime costs of generating electricity across different production methods (Raikar and Adamson, 2020).

In contrast to those factors, all the RE had a significantly lower impact than the non-RE in terms of emission (Hung, 2010), which aligns with the goal of the Paris Agreement. LCOE, emission and power density of power plants are the essential factors for policymakers to determine which power plant is the best to use in a specific area. Numerous research studies compare types of power plants with each factor separately. Most of the research is a comparative study between types of power plants or a causal analysis between chosen factors to develop a framework for decision-making.

(van Zalk and Behrens, 2018) has done a PRISMA transparent meta-analysis using snowball sampling. This study shows that increasing the RE portfolio will increase land use, presenting challenges for other sectors, such as agriculture and biodiversity. Formerly, (Matsuo et al., 2013) researched evaluating 9 (nine) different power sources in Japan based on their LCOE, sustainability and cost estimation. The study shows that the RE cost has decreased over the years, and Japan is massively developing their RE. Finally, (Abdallah and El-Shennawy, 2020) mentioned that emissions from power plants would be evaluated for Egypt's future development based on three scenarios. The result shows that the RE scenario will decrease Egypt's emissions below 30% by 2030. The above research shows that power densities, LCOE and emission are the main factors determining RE development.

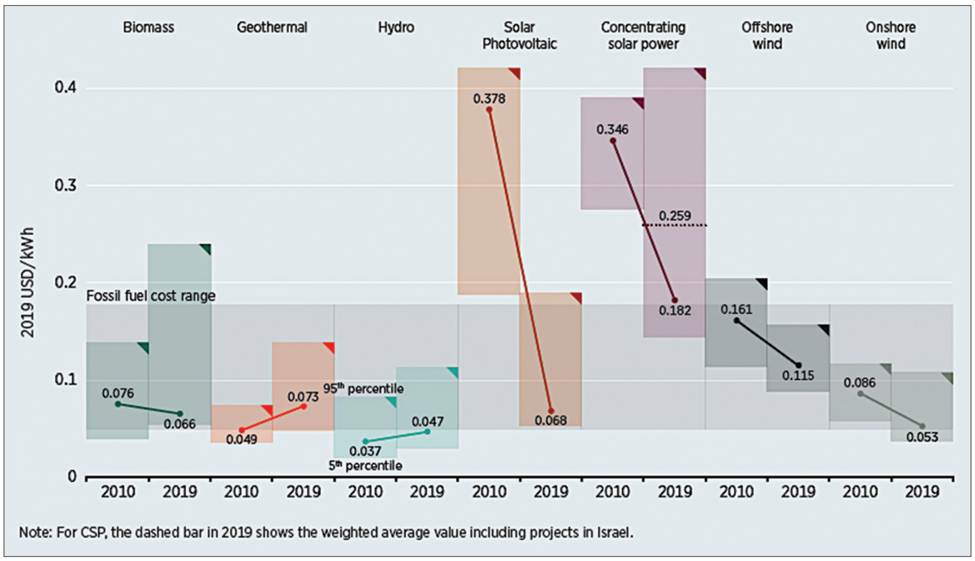
Formerly, Multi-Criteria Decision Making (MCDM) strategies have gained favor in energy supply systems, according to (Şengül et al., 2015), this article aims to create an MCDM framework for evaluating RE supply systems in Turkey. According to the findings, the amount of energy produced is the first criterion in Turkey's preference ranking of Renewable Energy Sources (RES), followed by ranking systems, land use, operation, and maintenance costs, installed capacity, efficiency, payback period, investment cost, job creation, and CO_2 emission value (Şengül et al., 2015). As a result of the MCDM analysis, the Hydro Power Station was declared Turkey's most RE supply system. Furthermore, the second, third, and fourth places are assigned to the Geothermal Power Station, Regulator, and Wind Power Station (Şengül et al., 2015). (Ulewicz et al., 2021) proposes an MCDM selection method that combines a qualitative pricing analysis with a fuzzy Analytical Hierarchy Process (AHP) and the technique for preference by similarity to an ideal solution (TOPSIS), integrated with a qualitative price analysis (ACJ). A case study on selecting a suitable RES in Polish industrial conditions was used to test this novel technique. According to the research, the proposed approach of determining the preferable RES can be applied in industrial firms that try to meet their energy needs while adhering to social responsibility standards (Ulewicz et al., 2021).

The process of choosing an appropriate power generation technology is intricate. It involves the consideration of diverse factors that are specific to each country. Policymakers typically conduct comprehensive feasibility studies and evaluations to determine the technology most effectively aligns with their country's requirements and circumstances. Policymakers should heavily rely on scientific research during their energy decision-making process to mitigate biases and promote decisions based on factual evidence and objective analysis. The method proposed in this research paper aims to attain an accurate solution.

Table 1: Land use for each energy technology (Buceti, 2014)

Technology	Gagnon/Bertani 2005 (Geothermal)		Fthenakis		McDonald (2030)		Smil		MacKay	Selected Values
	Land Use as m^2/kWh	W/m^2	Land Use as m^2/ kWh	W/m^2	Land Use as km^2/ TWh/y	W/m^2	Min (W/m^2) (MW/km^2)	Max (W/m^2) (MW/km^2)	W/m^2	W/m^2
Biomass Crops	5,33E-01	2,08E-01	1,25E-02	8,89E+00	5,43E+02	2,05E-01	5,00E-01	6,00E-01	5,00E-01	5,00E-01
Geothermal	5,00E-02	2,22E+00			7,50E+00	1,48E+01				2,22E+00
Hydro	1,52E-01	7,31E-01	4,00E-03	2,78E+01	5,40E+01	2,06E+00			2,40E-01	2,40E-01
Wind	7,20E-02	1,54E+00	1,50E-03	7,41E+01	7,21E+01	1,54E+00	5,00E-01	1,50E+00	2,00E+00	2,00E+00
Photovoltaic	4,50E-02	2,47E+00	3,00E-04	3,70E+02	3,69E+01	3,01E+00	4,00E+00	9,00E+00	1,00E+01	1,00E+01
Coal	4,00E-03	2,78E+01	4,00E-04	2,78E+02	9,70E+00	1,15E+01	1,00E+02	1,00E+03		2,78E+02
Gas			3,00E-04	3,70E+02	1,86E+01	5,97E+00	2,00E+0,2	2,00E+03		3,70E+02
Nuclear	5,00E-04	2,22E+02	1,15E-04	9,66E+02	2,40E+00	4,63E+01				9,66E+02

Figure 1: Global weighted average levelized cost of energy from utility-scale RE (IRENA, 2020)



This research will conduct a further analysis regarding a combined ranking of LCOE, emission and power density since the former research not considering power density and factors within LCOE such as payback period, investment cost, installed capacity and efficiency are separated in developing research. For instance, policymakers or prospective investors might wish to see measures of power plant suitability, given that constructing different types of energy sources has been shown to have a causal impact on power generation outcomes. Therefore, the ranking will be necessary to be analyzed. Hence, this paper expects to create an MCDM support framework for ranking optimum energy sources based on LCOE, power density and CO_2 emission. Firstly, the AHP method will select the parameter and alternatives based on the literature study. Next, the entropy method will obtain objective parameter weights from the information available within the data. At last, the TOPSIS method will be used to select the best RE alternative based on the performance of the three-parameter factors. In addition, there is a sensitivity analysis to test the effect of changes in factor parameters on changes in ranking.

The proposed technique can systematically handle the green energy sources selection process's contradictory, unstructured MCDM environment. This work is critical for decision-makers since it aims to provide critical insights for the administration of government, non-government, and corporate organizations working in the RE sector. The findings of this study can help governments and the public sector make informed decisions about various energy projects.

2. LITERATURE STUDY

2.1. Power Density

Comparing different energy sources has difficulty, like different dimensions—physics dimension account for their classification, either volumetric or flowing sources (Buceti, 2014). Energy density is the standard measurement used in comparisons between energy sources. Energy density is the energy (time rate of energy transfer) per unit volume (Jelley, 2019). The world is shifting from fossil-based fuels to clean energy systems, leading to a higher land use effect of energy systems (Bridge et al., 2013; Fouquet, 2016). (Smil, 2015) informs that RE produces energy in urban areas and industry at a small fraction of current power densities.

(van Zalk and Behrens, 2018) examines power densities in the United States for nine energy kinds and various sub-types (for example, solar power: PV, solar thermal). First, his study presents the aggregated results for all energy types and the underlying patterns. The power densities for renewable and non-RE resources are then studied within energy sub-types (van Zalk and Behrens, 2018). The time series regression and land-use projection results are then presented, finally Figure 2 shows an example application of these power densities to future NREL scenarios (van Zalk and Behrens, 2018).

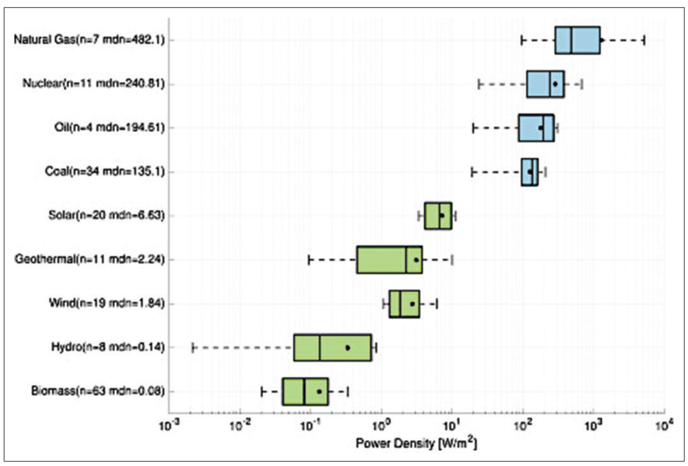
2.2. Levelized Cost of Energy (LCOE)

The LCOE is a standard metric for evaluating the costs of various power production systems (Raikar and Adamson, 2020). The value can be easily compared, which can assist people in business and policymakers in making decisions. The annuity technique is commonly used to compute LCOE because it allows for easy recalculation and assessment of the sensitivity of different factors to the LCOE outputs.

$$LCOE_{Annutizing} = \frac{Annual(cost)}{Average\ (output)} \tag{1}$$

$$LCOE_{Annutizing} = \frac{(\sum_{t=0}^{n} \frac{C_t}{(1+r)^t})(\frac{r}{1-(1+r)^{-n}}}{(\sum_{t=1}^{n} E_t)/n} \tag{2}$$

Figure 2: Average power density from various energy sources (van Zalk & Behrens, 2018)



Graph of LCOE (starting with LCOE 15.0, October 2021) for various energy sources as a function of the year, derived from Lazard's LCOE data (Lazard, 2021), Figure 3. With the increased implementation of RES, costs have declined in recent years, most notably for electricity generated by solar panels and wind turbines.

2.3. Emission

Our current electrical supply networks are material, fuel, and carbon-intensive, affecting the planet's greenhouse gas (GHG) balance (Stocker et al., 2013). When fossil fuels are burned, they release a substantial amount of carbon dioxide, one of the carbon emissions. Climate change is caused by carbon emissions, which trap heat in the atmosphere. A significant global effort is being conducted to decarbonise our energy system, to reduce global GHG emissions by at least 80% by 2050 (UNFCCC, 2016; Rogelj et al., 2016). Electrical sector emissions must be lowered to half of present levels by 2030 and to 85% by 2050 (OECD/IEA and IRENA, 2017). Based on the Intergovernmental Panel on Climate Change (IPCC) report, electricity and heat production contributed 25% of global GHG emissions, the highest among other economic sectors. There are many ways to reduce emissions from this sector, including RES and fossil fuels technology development. Hydropower, thermal- and PV-solar, onshore and offshore wind, biomass, geothermal, nuclear plants, natural gas, and clean coal with carbon capture and storage have all been modelled individually to achieve a low-carbon electricity system, with varying outcomes and accuracy for different technologies (Eom et al., 2015; Kis et al., 2018). In order to find out the impact of global warming caused by each power generation technology in the world, it is necessary to collect and compare the data on CO_2 emissions produced by each type of power plant. In this research, the data on CO_2 emissions (starting with LCOE 13.0, October 2019) for various energy sources as a function of the year are derived from Lazard's LCOE data (Lazard, 2019), Figure 4.

2.4. Rankings

According to the Oxford Dictionary, a ranking is a relationship between a set of items such that, for any two, the position of

Figure 3: Graph of levelized cost of energy (Lazard, 2021)

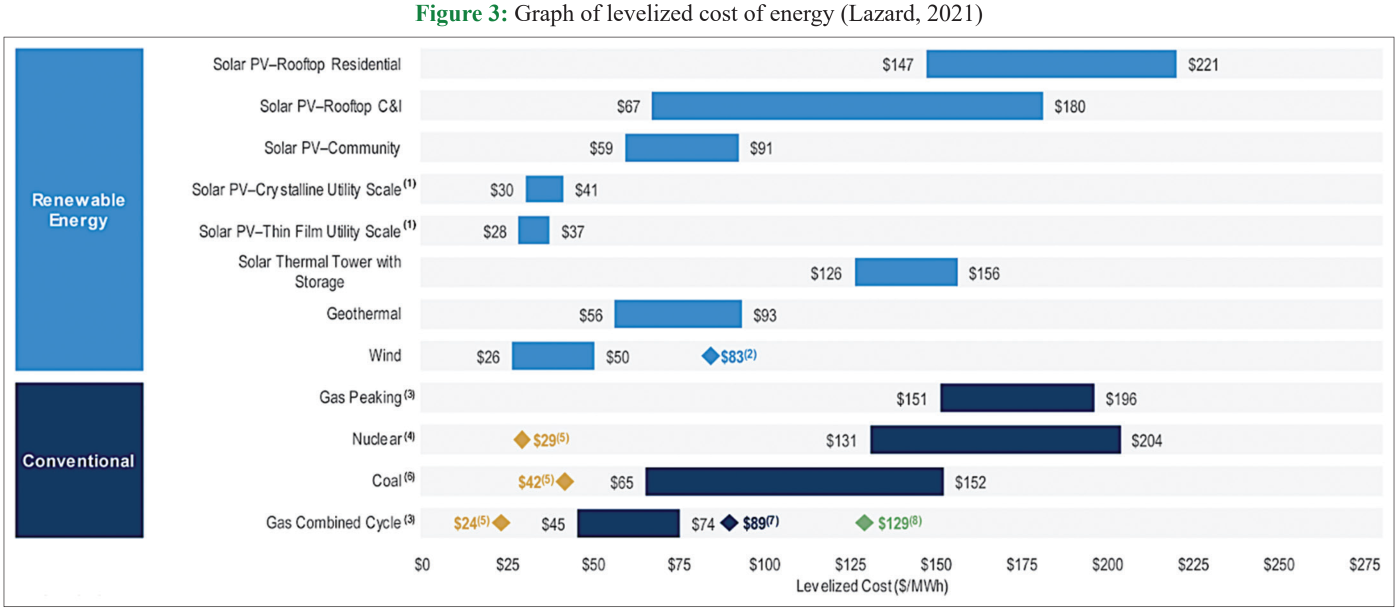


Figure 4: Data on CO_2 emissions (Lazard, 2019)

		Conventional Generation			Renewable Energy Generation			
	Units	Coal	Gas Combined Cycle	Nuclear	Wind	Solar PV Rooftop	Solar PV Utility Scale	Solar Thermal with Storage
Capital Investment/KW of Capacity (1)	$/kW	$2,975	$700	$6,900	$1,100	$2,800	$900	$9,100
Total Capital Investment	**$mm**	**1,993**	**560**	**4,209**	**1,111**	**8,232**	**1,476**	**7,462**
Facility Output	MW	670	800	610	1,010	2,940	1,640	820
Capacity Factor	%	83%	70%	91%	55%	19%	34%	68%
MWh/Year Produced (2)	**GWh/yr**	**4,888**	**4,888**	**4,888**	**4,888**	**4,888**	**4,888**	**4,888**
Levelized Cost of Energy	$/MWh	$66	$44	$118	$28	$151	$32	$126
Total Cost of Energy Produced	**$mm/yr**	**$322** 2	**$215**	**$576**	**$136** 1	**$740**	**$159**	**$618**
CO_2 Equivalent Emissions	Tons/MWh	0.92	0.51	—	—	—	—	—
Carbon Emitted	mm Tons/yr	4.51	2.50	—	—	—	—	—
Difference in Carbon Emissions	mm Tons/yr							
vs. Coal		—	2.01	4.51	4.51 3	4.51	4.51	4.51
vs. Gas		—	—	2.50	2.50	2.50	2.50	2.50
Difference in Total Energy Cost	$mm/yr							
vs. Coal		—	($107)	$254	($187) 4	$418	($163)	$296
vs. Gas		—	—	$361	($80)	$525	($56)	$403
Implied Abatement Value/(Cost)	$/Ton							
vs. Coal		—	$53	($56)	$41 5	($93)	$36	($66)
vs. Gas		—	—	($144)	$32	($210)	$23	($161)

something on a scale shows how good or critical they concern other similar things (Oxford University Press, n.d.). A rank reversal is a change in the rank ordering of the preferability of feasible alternative decisions when the technique of choosing or collecting other accessible alternatives changes, for example. Many discussions in decision-making, particularly MCDM, focused on the subject of rank reversals.

MCDM techniques are popular in energy-policy-making and policy ranking (Kumar et al., 2017). In addition, MCDM methods such as AHP have been used within the energy area analyses (Alizadeh et al., 2020). AHP is a simple yet powerful tool to support decision-makers in making more effective decisions by structuring and evaluating the relative attractiveness of competing preferences or alternatives (Handfield et al., 2002).

On the other hand, MCDM entropy has been used within energy area analyses to determine the weight of a criterion and estimate the preference of a parameter weight (Rubinstein and Kroese, 2004). The advantage of the entropy method is that the entropy method uses objective approaches to produce parameter weights based on data characteristics while simultaneously accommodating the subjective preferences of decision-makers (Figueira et al., 2016). Therefore, combining AHP with Entropy will allow decision-makers to subjectively and objectively evaluate parameter weights depending on various forms of decision data and levels of choice expertise (Al-Aomar, 2010).

After assessing criterion weight, another method is required to rank energy alternatives. Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) will be used to select the best option from a finite set by maximising distance from the ideal negative point while reducing the distance from the ideal positive point (Datta et al., 2014). In this case, TOPSIS requires a priority weight obtained from the entropy parameter weight to process further data.

Based on a literature study, the combination MCDM: AHP-Entropy-TOPSIS has never been used for RES ranking. This MCDM combination in research has been validated and recommended by experts. Furthermore, sensitivity analysis will be carried out to evaluate the robustness of the proposed methodology. The study of how the uncertainty in a mathematical model's output, system, or output variable can be allocated to multiple sources of uncertainty in its input variables is known as a sensitivity analysis (Saltelli et al., 2007). One of the sensitivity analysis methods that will be performed in this research is the Monte-Carlo simulation, which is included in global sensitivity analysis. (Saltelli et al., 2000) claim that Global Sensitivity Analysis (GSA) is the popular paradigm that has dominated modern-era sensitivity analysis for the past two decades. The four primary GSA methodologies are derivative-based, distribution-based, variogram-based, and regression-based GSA approaches (Tsvetkova and Ouarda, 2021). In this research, an expert team will be set up to determine initial subjective criteria weights then the entropy method will enhance it into objective criteria weights. This objective weight will rank the parameter of energy sources. Then, energy alternatives will be ranked based on the criterion weight.

3. RESEARCH METHODOLOGY

To attain unity of subjective and objective and to make the results more realistic and reliable, the entropy assessment approach considers the data and subjective preferences (Chuansheng et al., 2012). The step of this unified method is as follows:

Step 1 – Set an Expert Team: The team of experts consists of a group of people who are experts from several multi-disciplines related to energy, energy management, power systems, smart grid and distribution.

Step 2 – Establish a Hierarchical Model of the Problem: The first level of the hierarchical model states the goal, next level of the hierarchical model consists of policy parameters and is followed by the number of alternatives.

Step 3 – Determination of subjective criteria weight (AHP) using Pairwise Comparison: The initial weights of policy parameters are determined using a subjective method of AHP. AHP is commonly used to determine weights based on judgments (Basak and Saaty, 1993).

- AHP's purpose is to deconstruct the assessment framework into a hierarchical structure and compare each component against a set of guidelines. After that, get the comparison matrix components and figure out the relative and overall weights (Chuansheng et al., 2012).
- First, we must gather expert votes on each criterion and alternative. Each will then compare among measures and options to derive priorities using pairwise comparison.
- Then, we must compute subjective, relative importance weights (WS). If each expert's vote has equal importance, according to (Aczél and Saaty, 1983), geometric means the correct way for synthesising the judgments given by the experts as reciprocal matrices

$$f(x_1,x_2,..,x_n)=\sqrt[y]{q_1x_1^{\,y}+q_2x_2^{\,y}+..+q_nx_n^{\,y}} \tag{3}$$

Where $q_1 + q_2 + q_n = 1$, $q_k > 0$ ($k = 1, 2, n$), $y \neq 0$. Otherwise, q_1, q_2, q_n, and y are arbitrary constants.

- At last, we need to check the Consistency Ratio (CR) of synthesised pairwise judgments. CR denotes that the experts make a consistent decision by pairwise comparing parameters or options. If the level of inconsistency is acceptable, the synthesis stage combines the weight of parameters and options to compute an overall rating (CR ≤ 10%) (Chuansheng et al., 2012).

Steps 4 – Using Initial subjective criteria weight in Entropy and Determination of overall weight: The first step of Entropy is to determine parameters and initial weights of parameters carried out subjectively by the experts. These initial weights are derived from the Expert team's subjective weights. The following are the next steps in the Entropy method:

- After determining the parameter and initial parameter weights, a matrix must be made for each criterion, followed by normalisation of the weights specified in the initial matrix. Normalisation is the process of normalising the benefits and costs of each parameter.
- In case of the relative significance of indicators has nothing to do with that point, the relative significance of indicator j is measured by the following equation:

$$H(y_j)=-\sum_{i=1}^{n}\frac{1+y_{ij}}{y_j}\ln\frac{1+y_{ij}}{y_j} \tag{4}$$

Where $y_j=\sum_{i=1}^{n}1+y_{ij}$ and $\frac{1+y_{ij}}{y_j}<1$

- According to the nature of the entropy method, the equation above can be standardised at that point to get the Entropy which represents the significance of indicators:

$$e(y_j)=\frac{H(y_j)}{\ln n}=-\frac{1}{\ln n}\sum_{i=1}^{n}\frac{1+y_{ij}}{y_j}\ln\frac{1+y_{ij}}{y_j} \tag{5}$$

Where $0'' e(y_j)'' 1$

- According to the nature of Entropy, the smaller the esteem of $e(y_j)$, the greater the relative importance of indicator j. Therefore, in order to encourage the comprehensive assessment, the weight θ_j of indicator j can be calculated with the following equation:

$$\theta_j=\frac{1-e(y_j)}{m-\sum_{j=1}^{m}e(y_j)} \tag{6}$$

Where $0 \leq \theta_j \leq 1$ and $0\sum_{j=1}^{m}\theta_j=1$

Step 5 – Rank the power density, LCOE, and emission for every power generation: The analysis will get the evaluation results by using the value of entropy method, which means that the value of Entropy is the final weight of each parameter. Then the decision-maker can take this weight with their preference and get the final evaluation results using the TOPSIS method.

Step 6 – Alternative data normalisation: First, a decision matrix will be made based on the existing criteria information and then normalised using equation (7) to obtain a normalised decision matrix.

$$R_{ij}=\frac{D_{ij}}{\left[\sum_{j=1}^{M}d_{ij}^{\,2}\right]^{\frac{1}{2}}} \tag{7}$$

And then, the weighted normalised matrix is computed by multiplying the entropy criterion weights using the following equation.

$$h_{ij}=\theta_j R_{ij} \tag{8}$$

Step 7 – Performance and Distance measurement: The best and worst performance for each energy resource parameter is computed by choosing the maximum and minimum values using the following equations.

$$A^+=\{A_1^+,A_2^+,A_3^+,\ldots,A_M^+\} \tag{9}$$

$$A^-=\{A_1^-,A_2^-,A_3^-,\ldots,A_M^-\} \tag{10}$$

Because TOPSIS is a distance-based technique, all distances between the positive ideal solution (PIS) and negative ideal solution (NIS) are calculated using equations (11) and (12).

$$G_i^+=\sqrt{\sum_{j=1}^{f}(h_{ij}+A^+)^2} \tag{11}$$

Where $1 \leq i \leq f$, $1 \leq j \leq e$

$$G_i^-=\sqrt{\sum_{j=1}^{f}(h_{ij}-A^-)^2} \tag{12}$$

Where $(1 \leq i \leq f, 1 \leq j \leq e)$

Step 8 – Determine alternative ranking: For each energy resource option, relative closeness is calculated by multiplying the NIS value by the sum of the distances to the PIS, and the NIS value C_i is calculated using equation (13). C_i has a lot in common with the positive ideal solution. Alternatives are ranked according to the magnitude of C_i, with the option with the highest C_i receiving the top ranking among the others.

$$C_i = \frac{G_i^-}{G_i^+ + G_i^-} \tag{13}$$

Where $(1 \leq i \leq m)$

Step 9 – Sensitivity analysis: Sensitivity analysis, which considers the risks of changing alternative values, is further analysed to predict what would happen if an alternative parameter such as LCOE changes. Monte-Carlo simulation, included in variogram and distribution-based global sensitivity analysis, will be performed to analyse the effect of changing the input alternative's value on overall ranks.

4. RESULTS AND DISCUSSION

4.1. Set an Expert Team

The expert team consist of 30 persons from around the world from diverse educational backgrounds, such as a master, doctor and professor whose master in diverse disciplines such as power systems, energy system, energy management, and power distribution. In addition, these experts come from various institutions worldwide, such as government and professional, and contributed at all steps of our research where expert judgement is needed. The expert team will judge energy parameters and alternatives in this research as an input for AHP and entropy method.

4.2. Establish a Hierarchical Model of the Problem

In this step, the sequence of policy parameter and energy alternatives is structured into a hierarchy by building a problem framework of AHP that are easier to analyse and evaluate. The overall goal of this hierarchical model is to provide a decision-support framework for policy maker. Furthermore, the hierarchy helps structure the problem for the decision maker to rank the best energy alternatives. Figure 5 is the hierarchical model of this research.

As shown in Figure 5, the hierarchy presents three energy feasibility parameters and nine alternative energy sources and consists of three levels: Decision goal, decision parameter, and decision alternatives.

4.3. Determination of Subjective Weight

We first need to gather subjective pairwise comparison data from the experts to develop the sequence of policy parameters on three energy parameters. The data is then calculated equally for each expert. Finally, equation (3) is used to synthesise the judgements given by the experts. At last, we check the level of inconsistency and whether it is acceptable. The subjective criteria weight result of AHP is shown in Table 2. It is displayed that CO_2 emission level has the highest subjective criteria weight. The inconsistency ratio for the AHP subjective weight result is 0.04% which is acceptable because it is below 10%.

4.4. AHP's weight in Entropy and Determination of overall weight (AHP-Entropy)

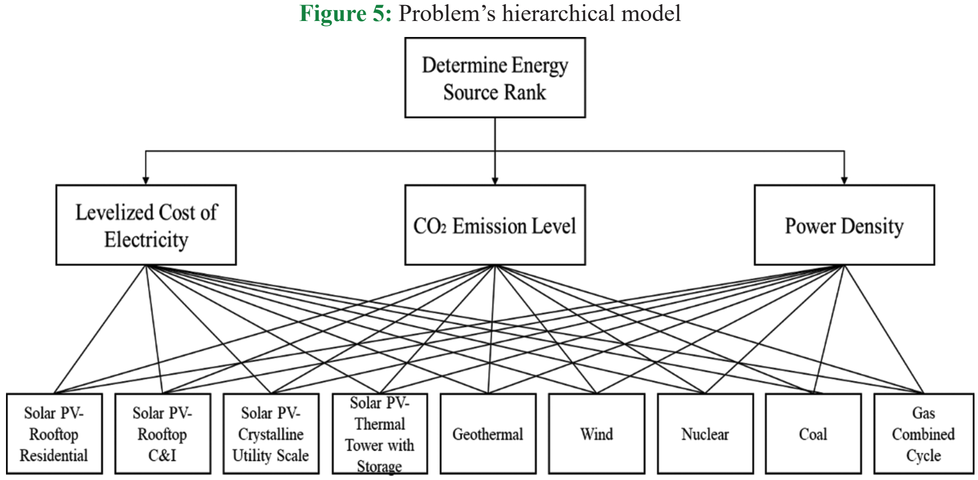
AHP's subjective criteria weight will then become the initial weight in the entropy method, Table 3. Nine alternative energy sources will be judged based on the data provided by Lazard's LCOE version 15.0 (Lazard, 2021) and 13.0 (Lazard, 2019) associated with LCOE, CO_2 emission level and a paper from van Zalk and Behrens, which discusses the power density of energy sources. The initial weight data from Lazard's report (Lazard, 2019; Lazard, 2021) and van Zalk and Behrens's paper (van Zalk and Behrens, 2018) will be normalised from the initial matrix. Table 4 shows the data normalisation of Entropy.

The entropy method is used to specify the objective parameter weights for energy parameters. Equation (5) is used to calculate Entropy for each criterion entropy ($e[y_j]$) as shown in Table 5. It can be inferred that parameter 2 has the highest entropy criterion value.

4.5. Rank The Energy Parameter

Equation (6) is then used to calculate the lambda value (θ_j), multiplied by the initial weight derived from AHP's subjective

Figure 5: Problem's hierarchical model



result. The table below shows the entropy objective weight result of the research, which determines the sequence of energy parameter.

Table 6 shows that parameter 1, LCOE, has the highest objective weight based on data provided by Lazard (Lazard, 2019; Lazard, 2021) and van Zalk and Behrens's paper (van Zalk and Behrens, 2018).

4.6. TOPSIS Alternative Ranking

Entropy's parameter weight will then become the reference in the TOPSIS alternative ranking. Nine alternative energy sources will be judged based on the data provided by Lazard's LCOE version 15.0 (Lazard, 2021) and 13.0 (Lazard, 2019) for LCOE and CO_2 emission levels and van Zalk and Behrens' paper (van Zalk and Behrens, 2018) for power density. Table 7 shows the alternative's initial weight. The initial weight data is in the form of uniform distribution, where the data has a minimum and maximum range. These data will then be normalised from the initial matrix. Table 8 shows the data normalisation of TOPSIS. TOPSIS method is then used to determine performance and distance measurement for each alternative. Equation 7 and 8 is then used to calculate the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS), as shown in Table 9. Equation (9) is then used to calculate the C_i value, which resembles the positive ideal solution.

Alternatives with the biggest C_i will hold the highest rank among other alternatives. Table 10 shows the TOPSIS Alternative ranking. From Table 10, it can be inferred that alternative 9, combined cycle gas, has the highest weight. In this research, TOPSIS alternative weight is the final result of this research method. Furthermore, sensitivity testing will be performed to test the effect of changes in factor parameters in ranking change. The test will be performed

Table 2: AHP subjective weight result

Parameter	C_1	C_2	C_3	Weight
LCOE (C_1)	1	0.96	1.19	0.347
CO_2 emission level (C_2)	1.03	1	1.35	0.37
Power density (C_3)	0.83	0.73	1	0.282

AHP: Analytical hierarchy process, LCOE: Levelized cost of energy

Table 3: Entropy initial weight

No	Parameter	Code	Category	Weight
1	Levelized cost of electricity	C_1	Cost	0.347
2	CO_2 emission	C_2	Cost	0.37
3	Power density	C_3	Benefit	0.282
Total				1

Table 4: Entropy data normalisation result

Energy sources	Data normalisation		
	C_1	C_2	C_3
	Cost	Cost	Benefit
Solar PV-rooftop residential	0.2	1	0.6
Solar PV-rooftop commercial and industrial (C&I)	0.25	1	0.6
Solar PV-crystalline utility scale	1	1	0.4
Solar thermal tower with storage	0.25	1	0.2
Geothermal	0.5	1	0.2
Wind	0.333	1	0.2
Nuclear	0.2	1	1
Coal	0.333	0.25	1
Gas combined cycle	0.5	0.333	1
Total	3.567	7.583	5.2

Table 5: Entropy criterion value

Entropy criterion value	
Parameter	Value
C_1	0.931
C_2	0.964
C_3	0.92
Total	2.816

Table 6: Entropy objective weight result

Parameter	C_1	C_2	C_3
θ_j	0.402	0.219	0.377
Rank	1st	3rd	2nd

Table 7: Alternative initial weight (Lazard, 2019; Lazard, 2021; van Zalk and Behrens, 2018)

Energy sources	Initial weight		
	C_1	C_2	C_3
	Cost	Cost	Benefit
Solar PV-rooftop residential	18.4	0	9.9
Solar PV-rooftop C&I	12.35	0	6.85
Solar PV-crystalline utility scale	3.55	0	5.95
Solar thermal tower with storage	14.1	0	5.95
Geothermal	7.45	0	7.51
Wind	3.8	0	2.185
Nuclear	16.75	0	148
Coal	10.85	11	100
Gas combined cycle	5.95	4.12	775

Table 8: TOPSIS data normalisation result

Energy sources	Data normalisation		
	C_1	C_2	C_3
Solar PV-rooftop residential	0.518	0	0.012
Solar PV-rooftop C&I	0.348	0	0.008
Solar PV-crystalline utility scale	0.091	0	0.007
Solar PV-thermal tower with storage	0.397	0	0.007
Geothermal	0.21	0	0.009
Wind	0.233	0	0.002
Nuclear	0.472	0	0.186
Coal	0.305	0.874	0.125
Gas combined cycle	0.167	0.484	0.974

TOPSIS: Technique for order of preference by similarity to ideal solution

Table 9: TOPSIS performance and distance measurement

Energy sources	Data normalisation	
	D_{j+}	D_{j-}
Solar PV-rooftop residential	0.402	0.205
Solar PV-rooftop C&I	0.378	0.217
Solar PV-crystalline utility scale	0.365	0.268
Solar PV-thermal tower with storage	0.385	0.211
Geothermal	0.367	0.241
Wind	0.367	0.266
Nuclear	0.334	0.217
Coal	0.390	0.099
Gas combined cycle	0.081	0.414

TOPSIS: Technique for order of preference by similarity to ideal solution

Figure 6: Coal energy rank sensitivity tornado diagram

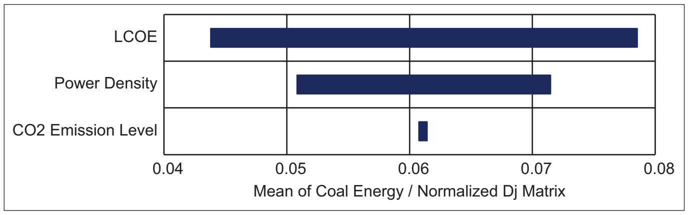


Figure 7: Wind energy percent change inputs diagram

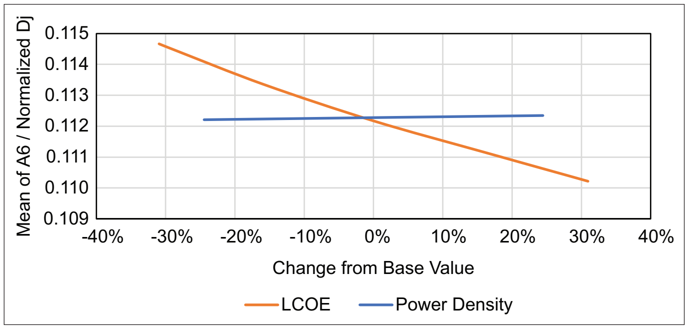


Table 10: **TOPSIS alternative ranking**

Energy sources alternatives	Normalised D_j	Rank
Solar PV-rooftop residential	0.090	8
Solar PV-rooftop C&I	0.097	6
Solar PV-crystalline utility scale	0.113	2
Solar PV-Thermal tower with storage	0.095	7
Geothermal	0.106	4
Wind	0.112	3
Nuclear	0.105	5
Coal	0.054	9
Gas combined cycle	0.223	1

TOPSIS: Technique for order of preference by similarity to ideal solution

in Table 10's "Normalised D_j" value for 1000 iterations through 21 simulations. Each simulation result will be ranked, and the number of alternatives rank change will be calculated. This simulation will test changing the alternative value's effect on the alternative rank. Figures 6 and 7 show the tornado diagram and per cent change diagram of coal and wind energy, while Table 11 will show the rank change possibility of alternatives in this research.

As shown in the tornado diagram in Figure 6, can be inferred that LCOE is the most sensitive factor for coal energy, the most significant ranking change factor, followed by its power density and emission level. Tornado diagrams have the function of comparing the relative importance and impact of various variables with uncertainty. One difference between fossil energy and RE in sensitivity analysis is that there is no change in emission levels in RES because the minimum and maximum values are 0.

From Figure 7, it can be inferred that LCOE from wind energy sources has a significant range of Normalised D_j changes compared to its power density. As mentioned before, RE does not emit emissions during its operation, so that the emission value will remain 0. Therefore, the range of changes in the average "Normalised D_j" means from wind energy sources caused by changes in LCOE ranges from 0.110 to 0.114, while the change caused by power density ranges from 0.1122 to 0.1123.

Table 11: **Rank change possibility**

Energy sources alternatives	Number of rank changes	% change
Solar PV-rooftop residential	0	0.0
Solar PV-rooftop C&I	4	19.0
Solar PV-crystalline utility scale	5	23.8
Solar PV-thermal tower with storage	3	14.3
Geothermal	3	14.3
Wind	4	19.0
Nuclear	9	42.9
Coal	0	0.0
Gas combined cycle	0	0.0

From Table 11, it can be inferred that nuclear energy has the highest rank change possibility with 42.9%, followed by solar PV-crystalline utility scale with 23.8% and solar PV-rooftop C&I with wind energy with 19.0% rank change possibility. The per cent rank change is derived from the number of rank changes divided by the number of simulations, which is 21. This result can be used as a consideration for decision-makers in deciding on policies to be implemented based on ranking and sensitivity analysis results.

5. CONCLUSION

From the comprehensive evaluation result, LCOE weight is the highest among the three parameters, followed by power density and CO_2 emission level. After analysing a set of multiple energy source data related to LCOE, CO_2 emission, and power density provided by Lazard (Lazard, 2019; Lazard, 2021) and a paper from van Zalk and Behrens (van Zalk and Behrens, 2018), gas combined cycle ranks the highest among other alternatives, followed by solar PV-crystalline utility-scale, geothermal, wind, nuclear, solar PV-rooftop C&I, solar PV-thermal tower with storage, solar PV-rooftop residential.

Sensitivity analysis shows that only gas combined cycle, coal and solar PV-rooftop residential will remain in the same rank if input changes. Meanwhile, nuclear energy has the highest possibility of rank change with 42.9% of change based on the simulation, followed by solar PV-crystalline utility-scale, wind and solar PV-rooftop C&I.

This energy ranking serves as an initial reference for stakeholders in the energy sector to develop power generation infrastructure that optimises local energy utilisation. Thus, this research can be used to increase objectivity in the assessment and selection of power generation technology to be implemented.

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