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THE IMPLEMENTATION OF AHP AND WHALE OPTIMIZATION ALGORITHM IN THE SELECTION AND OPTIMIZATION OF BEST CLEAN ENERGY SOURCE

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Abstract
Clean energy sources have become more and more important in the present time, especially with the goal to reduce the production of greenhouse gases. There are various clean energy sources available, and care must also be taken into which clean energy source is more prevalent in which location. Furthermore, with the multiple alternatives for such clean sources, a method has to be developed to choose the best one, and, if possible, have it optimized to produce the best performance. It is also good if the method developed only requires theories without any need of practical applications in real life (although this is strongly encouraged). This paper will show the utilization of a decision-making tool, namely the analytic hierarchy process, to decide the best energy source and which components are important and then conducts the optimization process through whale optimization algorithm. The research will then conclude with the best energy source chosen in its optimized state. It is hoped that this research will open a gateway into determining which energy sources to use digitally without any recourse to incurring costs on its way.

Keywords:
Decision analysis; optimization algorithm; clean energy

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1. Introduction

Renewable energy sources have become quite important today, as the world now moves to produce cleaner energy. This falls in line with some of the Sustainable Development Goals (SDG) set out by the United Nations (UN), which are (Osborn et al., n.d.):

- Goal 7: Ensure access to affordable, reliable, sustainable, and modern energy for all
- Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation
- Goal 13: Take urgent action to combat climate change and its impacts

Note that there may be other SDGs that are applicable to this research. However, the three SDGs listed above are the most relevant ones.

There are various types of energy available to achieve the SDGs mentioned. These are hydro, solar, wind, biomass, nuclear, and geothermal. These sources are different to each other based on certain characteristics, which prove to be a challenge when determining which one is best to utilize. Moreover, it must also be considered where the renewable energy sources are going to be used, as each geographical area will have different parameters. In this paper, the country that these renewable energy sources will be based on is Indonesia.

Indonesia has already made strides to produce clean energy; this can be observed when the country joined the Clean Energy Demand Initiative (CEDI). It also has goals to achieve within specific timeframes:

- Nationally determined contribution (NDC) in 2030
- Net zero emissions (NZE) in 2060

- 23% renewable energy in primary energy mix in 2025

However, since energy is highly dependent upon for human survival, it is only natural that the most practical sources of energy are used based on the resources available in the country. This means that fossil fuels are still used (coal, oil and gases). In the year 2020, they constituted 88.7% of the primary energy supply, whereas all the renewable energy sources combined total at 11.3%. By looking at one of the goals that needs to be achieved, Indonesia needs 11.7% more renewable energy sources in the primary energy mix. The prediction whether it is possible to be achieved in a span of 5 years is outside the scope of this study and will not be discussed in-depth.

According to [2], there are nine types of fuels that are used for energy consumption in Indonesia: coal, oil, natural gas, hydro, geothermal, solar energy, wind energy, biofuel, biogases. However, nuclear power is not used as a source of energy yet. Even though it is clean and sustainable, considerable public opposition goes against the usage of this energy source. There are two major reasons for this opposition [3]:

- Multiple hazards and/or accidents may surface (nuclear accidents and weapons, radioactivity)
- The public was not active in the engagement of the decision-making of nuclear power which may lead to public mistrust

However, for this paper, nuclear energy will be included as one of the possible clean energy sources. This is since nuclear energy may be a key solution to energy sustainability in Indonesia, despite the apparently large public opposition against such source. With all these available clean energy sources, it must be known which source is the best one to be used.

This study is significant in two ways: the first is providing an alternative way of optimizing the available renewable sources and the second is developing a greater understanding as to how mathematical modelling and optimization algorithms have a role in such activity. Three research problems are also present: determining the best clean energy source, optimizing the best clean energy source and developing a suggested framework on such procedure. Lastly, three objectives must be met in this research: determining the key performance indicators (KPIs) to choose the best clean energy source, conducting decision-making process for best clean energy source and parameter prioritizations, utilizing Python for whale optimization algorithm application.

Therefore, to resolve the research problems and achieve the research objectives, a two-step method is implemented: the first step is to select the best clean energy source through analytic hierarchy process (AHP), a decision-making tool. The AHP components will be based on the input of two experts in the field of clean energy sources. After the best clean energy source has been chosen, then its parameters will be optimized through the whale optimization algorithm (WOA). The weighting of the parameters that need to be optimized is based on the input of one of the experts.

2. Methods

This chapter consists of the methods conducted to perform the research. It can be broken down into three phases: decision analysis, optimization, evaluation. The decision analysis consists of an explanation of how the AHP is performed. The optimization process explains the development of the energy cost model (along with its components' models) and its integration into the WOA, as well as its verification through Python. The integration of AHP and WOA is perfectly acceptable, as AHP could be "used in a particular case as a sole method or in combination with other notable systems or methods" [11]. The evaluation phase will indicate how the performance metrics are evaluated and how the suggested framework will be developed based on the findings.

A. Methodology Framework

Fig. 1 shows the framework of the research methods utilized in this work.

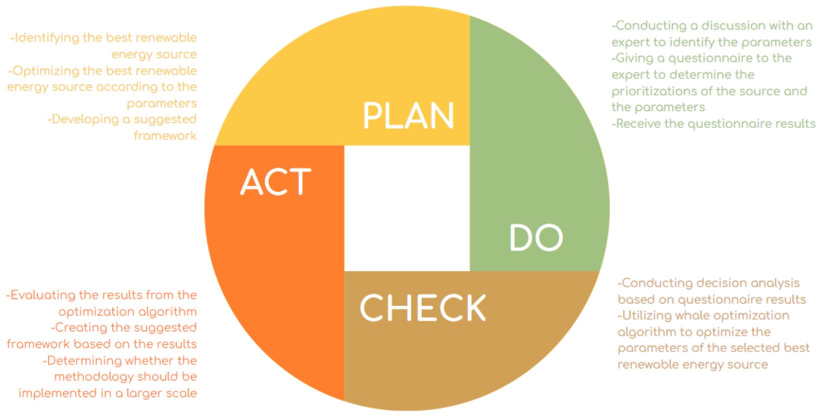

Figure 1. PDCA Framework

A strong structured framework is needed to ensure that the research will be conducted smoothly, outlining the activities clearly in each phase. Therefore, the Plan-Do-Check-Act (PDCA) framework is utilized. The explanations for the framework are as follows:

- Plan: this is where the problems of the research are stated, and the plan will be implemented.
- Do: the plan is implemented at a small scale, in this case Indonesia.
- Check: an evaluation of the results is conducted.
- Act: a suggested framework is developed which may indicate whether the process should be implemented at a larger scale.

B. Decision Analysis

The decision analysis conducted for this research is in the form of AHP. It is a type of multi-criteria decision-making method (MCDM), which is “a well-structured and multidimensional process developed to tackle decision-making problems in different fields and search for the most attractive alternative with consideration of all relevant criteria” [9]. AHP also has great availability in literature in its application. As such, this method will be used to select the best clean energy source. AHP is utilized as a decision-making tool because there are not many criteria and alternatives present in the decision system. As such, a sophisticated decision system (e.g., a combination of decision-making systems) is not needed for such decision processing: a simple and practical tool will suffice.

The process of AHP is developed by Thomas Saaty, which comprises of five steps [10]. First, the hierarchy model should be developed that will consist of goal (the objective), the alternatives (possible ways to achieve such objective), and the criteria (evaluations of the alternatives). Second, prioritizations will have to be set as weights for the criteria, which will then be used in pairwise comparisons. Third, the judgments will then be synthesized to produce a set of priorities for the hierarchy through combining the judgments of the criteria. Fourth, the judgments’ consistency will be evaluated with inconsistency ratio. Fifth, the final decision will then need to be made based on the results received.

The building be simply denoted shown in Fig. 2.

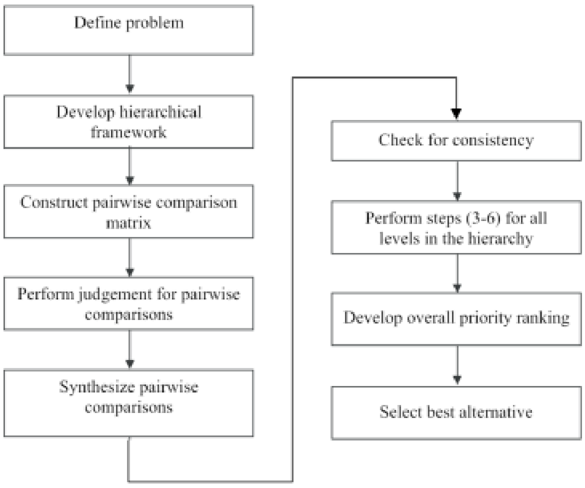

Figure 2. AHP Method Steps (Budiman & Pratama, 2022)

AHP has advantages that made it one of the common MCDM methods to use:

1. Only a pair of elements is needed in each instance of time, despite the numerous factors that may be involved in the situation.
2. Allows the inclusion of tangible variables and intangible variables (or, in other words, quantitative and qualitative).

Naturally, there are limitations to the AHP method. According to [7], there are two main issues:

1. Rank reversals: the method of rank reversals apparent in the AHP method means that if any alternative is added or deleted, then the relative rankings of the other alternatives will change.
2. Condition of order and preservation (COP): due to the priorities in AHP being derived from the eigenvector values, the COP is violated. As stated by Thomas Saaty: "For all alternatives x_1, x_2, x_3, x_4, such that x_1 dominates x_2 and x_3 dominates x_4, then the vector of priorities w should be such that not only $w(x_1) > w(x_2)$ and $w(x_3) > w(x_4)$ (preservation of order preference) but also that $w(x_1) / w(x_2) > w(x_3) / w(x_4)$ (preservation of order of intensity of preference)" (Saaty, 2013 as cited in [7]).

But even with the limitations listed above, AHP remains a powerful and common method in decision-making, showing that its limitations can be mitigated in various ways.

As mentioned before, criteria and alternatives are in an AHP system and so they need to be determined. The criteria for the AHP method are in the form of KPIs. There are various KPIs that characterize clean energy sources, which must be discussed later with an expert in this field.

As for the alternatives, there are different types of clean energy sources that are available to use. The purpose of the AHP method is to select one of these alternatives as the best clean energy source to use. There are six clean energy sources for consideration in this research:

- Hydro
- Solar
- Wind
- Biomass
- Nuclear
- Geothermal

After identifying the number of criteria as well as the details regarding the alternatives, the structure of the AHP can now be developed. It is shown in Fig. 3.

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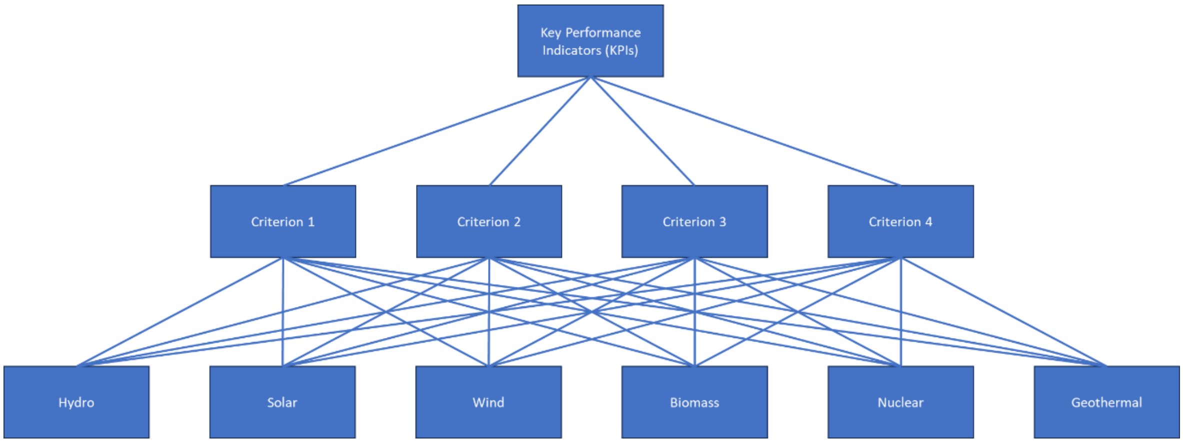

Figure 3. AHP Structure

AHP will be able to select the best alternatives using prioritizations. The criteria won't be equal in importance when compared to each other, and so prioritizations are needed, which are in the form of relative weights (relative since "the obtained criteria priorities are measured with respect to each other" [6]. These prioritizations are the results of pairwise comparisons, which mean that the judgments must be input for both criteria and alternatives. Pairwise comparisons can be understood using matrix, where a "pairwise comparison matrix A is a *m* x *m* real matrix, where *m* is the number of selected criteria." (Saaty, 1980 as cited in [4]). It also has several terms that needed to be understood. In the pairwise comparisons, "each entry a_{jk} of the matrix A represents the importance of the *jth* criterion relative to the *kth* criterion, where a_{jk} denotes the entry in the *jth* row and the *kth* column of A" (Saaty, 1980 as cited in [4]).

These judgments are given by two experts in this field. These experts act as decision-makers (or also known as domain experts), who will give judgment through a Google Form questionnaire, directly completing pairwise comparisons for the independent elements in the hierarchical structure. The judgments are made based on the comparison between multiple criteria and multiple alternatives. For example, geothermal will be compared with solar and the expert will judge which is more important than the other.

The levels of importance in the criteria and alternatives' comparisons that the expert will give are based on the Saaty scale. The judgment points and their explanations are shown below [10]:

- 1: equally important (the two variables have equal contribution to the objective)
- 3: moderately important (one element is moderately favored more than the other in terms of experience and judgment)
- 5: strongly important (one element is strongly favored more than the other in terms of experience and judgment)
- 7: very strongly important (one element is very strongly favored more than the other, where its dominance is clearly apparent)
- 9: extremely important (one element is favored more than the other in the highest possible order of affirmation)

In other papers, 2, 6, and 8 are also used as judgment points to represent intermediate values, but they are not used in this paper.

After gathering the judgments, the answers will be input into the SuperDecisions software. The reason why this software is chosen is because of the ease of use in conducting the pairwise comparison matrix methods; the experts' judgments can be input and then the decision results are immediately available. The outputs will be the prioritizations of the criteria and the alternatives. The prioritizations of the criteria come in the form of weights, which will then be used to determine the weight values of the variables in the energy cost model later. However, for the alternatives, the prioritizations themselves are the only information needed. Consideration of the inconsistency ratio of the answers must be considered, in which the recommended threshold is <10%. But this is another important limitation of AHP, in its consistency matrix. The AHP method "can only be sued for consistent decisions, and it is an important advantage if we want to avoid contradictions, but not all decisional problems can be consistent" [4]. Therefore, it is to be noted that even though consistency is important in judgments, there are certain situations in which a higher inconsistency ratio (even up until 30%) may warrant acceptance. These situations are when accurate answers are more important than consistent ones.

According to [13], the formula for the consistency index (CI) calculation is:

$$CI = \frac{(\mu_{max} - n)}{(n-1)} \quad (1)$$

where μ_{max} is the biggest eigenvalue. The formula for the consistency ratio (CR) is as follows:

$$CR = \frac{CI}{RI} \quad (2)$$

where CI is consistency index and RI is random index, which is the "consistency index of a randomly generated pairwise evaluation matrix" [13].

C. Whale Optimization Algorithm

Whale optimization algorithm is a metaheuristic algorithm inspired by the hunting nature of the humpback whales. The hunting nature can also be termed as bubble-net feeding method, in which two maneuvers are involved: 'upward-spirals' and 'double-loops'. According to [8], they "dive around 12 m in the former maneuver and then start making bubble in a spiral shape around the prey and swim up toward the surface". As for the second maneuver, three stages are enacted: coral loop, lob-tail and capture loop. Fig. 4 shows the humpback whales' bubble-net feeding behavior.

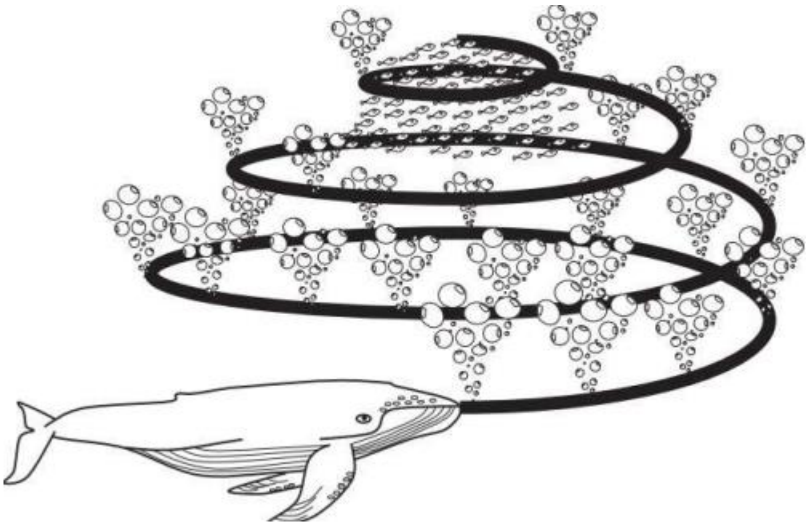

Figure 4. Humpback Whales' Bubble-Net Feeding Behavior [8]

It is one of the relatively simple algorithms to utilize and it has comparable better performance, which is why it has been chosen instead of its more famous counterparts, such as genetic algorithms. It was developed quite recently in 2016, but it already started being used increasingly throughout the years, as can be seen in Fig. 5.

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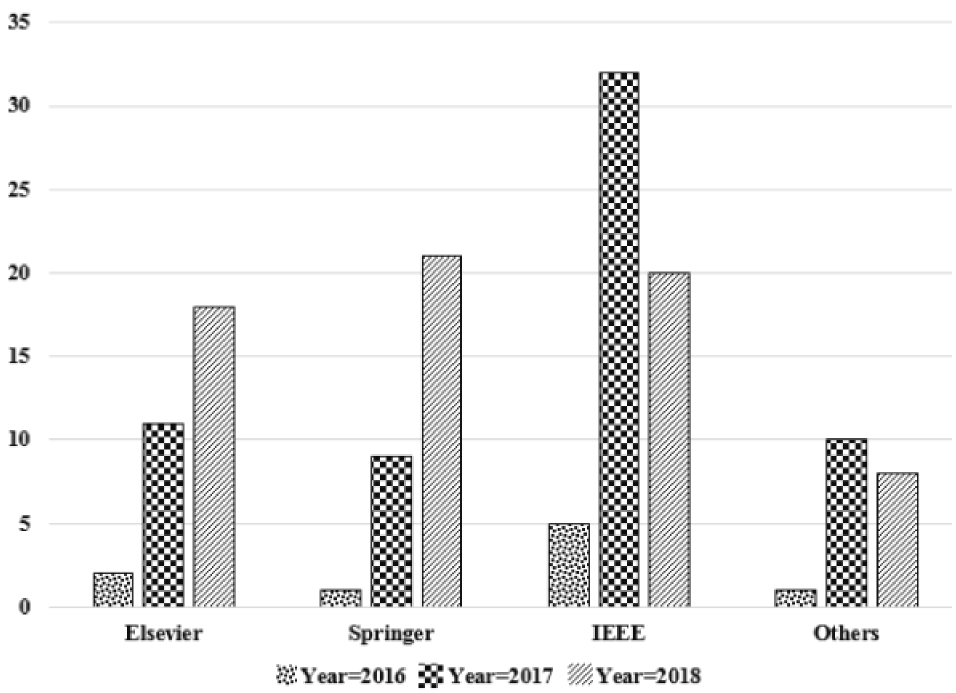

Figure 5. Trends of WOA Application [8]

There are three phases in whale optimization algorithm: exploration phase, encircling prey, and exploitation phase. The exploration phase means the diversification of the search space and the exploitation phase refers to the intensification of the best agent [12]. In this algorithm, the whales represent the solutions (note that the algorithm is composed of a set of solutions), and the main objective is for a whale to try to fill a new place in the search space that is considered the best in that current instance.

In the exploration phase, a whale globally searches for the best solution in a random manner. Its mathematical model is shown in (3).

$$V(k+1) = V_{random}(k) - Y * D \tag{3}$$

where V is position vector, k is current iteration, Y is coefficient vector, and D is distance. To calculate the coefficient vector, the formula is shown in (4).

$$Y = 2 * l * \beta - l \tag{4}$$

where Y is coefficient vector, l is decreasing linear value within the range [2, 0] and β is random value within the range [0, 1].

The exploration phase model also requires that the distance be calculated. Eq. (5) showcases how the distance can be calculated.

$$D = |X * V_{random}(k) - V(k)| \tag{5}$$

where D is distance, X is the coefficient vector, k is the current iteration. The formula also requires X to be determined, which is calculated using (6).

$$X = 2 * \beta \tag{6}$$

where X is coefficient vector and β is random value within the range [0, 1].

The second phase is the encircling prey. This is when the whale settles on a target as the best solution and informs other whales to focus on it. The mathematical modelling is the same as the one in the exploration phase mathematical model, however the random value of the position vector is replaced by the best position vector value. The formulation is shown in (7).

$$V(k+1) = V_{best}(k) - Y * D \tag{7}$$

where V is position vector, k is current iteration, Y is coefficient vector, D is distance. Calculating Y and D is the same as the one in the exploration phase mathematical model.

The final phase is the exploitation phase, in which there are two possible approaches: the shrinking circle and the spiral approach. This phase is used to produce the whales' bubble net behavior. The first part, the shrinking circle, determines the possible new positions of search agents that lie between the original position and the current best solution [14]. The spiral approach is slightly different, in that it does not focus on the new search agent positions between the original and the current best. Rather, this approach is to "mimic the helix-shaped movement of humpback whales" [14]. The formulation of the spiral approach is shown in Equation 8.

$$V(k+1) = \begin{cases} V_{best}(k) - Y * D \ if \ P < 0.5 \\ D * e^{mn} * \cos(2\pi h) + V_{best} \ if \ P \geq 0.5 \end{cases} \tag{8}$$

where m is a constant defining the logarithmic shape and n is the random number within the range [-1, 1].

With the information listed above, it can be surmised that WOA does have important advantages over its relatives. It has a high exploration ability as well as high exploitation and convergence, leading to its ability of avoiding high local optima and convergence speed during each iteration [5].

D. Energy Cost Model

The energy cost model is based on the KPIs that were going to be determined through a discussion with an expert. The energy cost model is shown in (9).

$$E = \alpha A + \rho B + \gamma C + \varphi D \tag{9}$$

where E is energy consumed, A is the first criterion, B is the second criterion, C is the third criterion, D is the fourth criterion. α, ρ, γ, φ are the weights used for the criteria, each used respectively. It is also important to note that this energy cost model seeks to optimize the energy cost through the minimization process.

The weights are determined through the decision analysis results. And since this model is utilized without any direct experimentation, each of the variables will be determined through probabilistic models.

The optimization process will be conducted through a programming language, namely Python. Python is software that allows users to be flexible in developing algorithms, such as whale optimization algorithm, which will be used for this research.

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3. Result and Discussion

A. Decision Analysis

After a discussion with an expert, the four criteria for the selection of the best clean energy source have been determined. They are:

- Efficiency (%): this is based on the efficiency of the energy source in terms of producing energy. As it is desirable to have a highly efficient energy source, this leads to the belief that the higher the efficiency of the energy source, the more appealing it is.
- Levelized cost of energy ($/MWh): the levelized cost of energy refers to the how much energy should be sold for the break-even to occur at the end of its physical lifetime.
- Location site (km): this refers to the distance between the location site of the energy source and transportation lines/city. This is an important parameter regarding the maintenance of the energy source as well as the distribution of the energy to both urban and rural areas.
- Capital cost ($): the cost required to start the generating of the energy source. This is important due to the energy source needing capital for it to begin functioning (without the funds, no energy source can begin generating).

As the criteria are already identified, it is now possible for the AHP structure to be updated. Fig. 6 showcases the updated AHP structure.

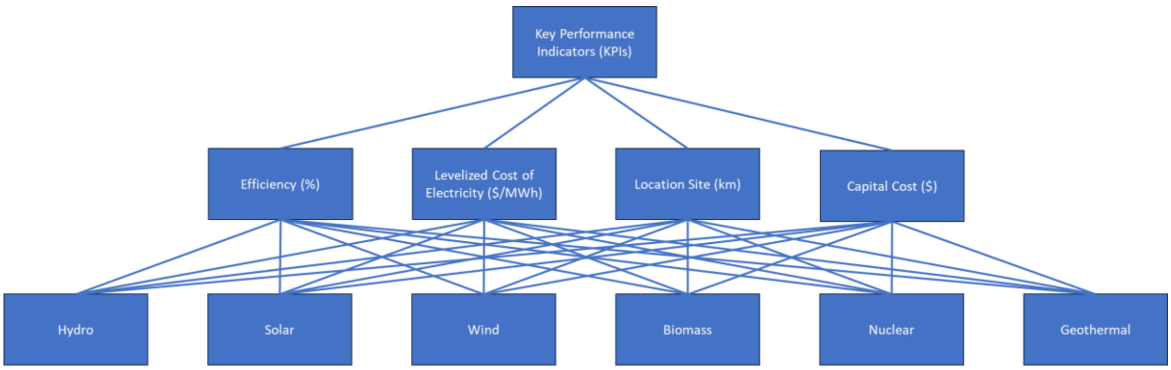

Figure 6. Updated AHP Structure

Since the AHP structure is already complete, now the AHP structure can be inserted into the SuperDecisions software. Fig. 7 shows the SuperDecisions layout for the AHP.

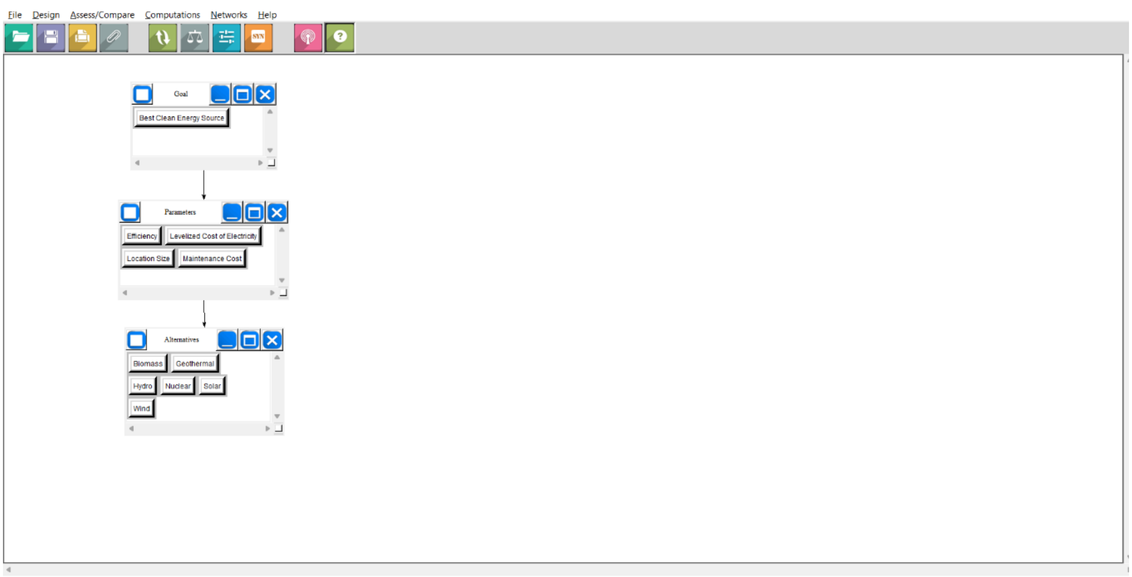

Figure 7. The AHP Layout in SuperDecisions

In SuperDecisions, the judgments that the experts gave (1, 3, 5, 7, and 9) are input into the pairwise comparisons window of the software (a sample is shown in Fig. 8). For the pairwise comparisons, two experts have given the judgments, which are then combined. The results of the priority weights for the alternatives are shown on Table 1.

Figure 8. SuperDecisions Pairwise Comparisons Window Sample

Table 1. Priority Weights of the Alternatives

KPIs	Priority Weights
Hydro	0.23105
Solar	0.09960
Wind	0.11199
Biomass	0.14670
Nuclear	0.28041
Geothermal	0.13025

As can be seen on Table 1, nuclear has the highest priority weight as compared to the other alternatives, meaning that nuclear power is the best alternative (according to the judgments) and this energy source is the one that will proceed to the next stage: optimization.

It is also imperative that the inconsistency ratio is identified for all those involved in the decision-making process. It was previously mentioned that the recommended threshold is 10% or less. However, if the situations warrant so, the threshold can be enlarged to even 30%. According to the result of the AHP, the inconsistency ratio of Table 2 showcases the inconsistency ratios for the criteria.

Table 2. Inconsistency Ratios of the Criteria

KPIs	Priority Weights
Efficiency (%)	7.90%
Levelized cost of electricity ($/MWh)	3.32%
Location site (km)	18.0%
Capital cost ($)	9.77%

Efficiency, location site, and capital cost have inconsistency ratios below 10%, which meant that that answers remain consistent throughout. For the location site, the inconsistency ratio is over 10%, meaning that its inconsistency is concerning. It is acceptable, however, if consideration is taken on who gives the judgment in that area: an expert with decades of experience in the field of energy. After considering the situation, the accuracy of the answers is more important than that of its consistency. Since the inconsistency is not quite significant from that of the threshold, it is therefore acceptable for the location site's results to be further processed.

Now, the priority weights for the key performance indicators (KPIs) of the energy sources are needed. Priority weights are important for updating the energy cost model and, later, the optimization itself. The values are shown on Table 3.

Table 3. Priority Weights of KPIs

KPIs	**Priority Weights**
Efficiency (%)	0.44191
Levelized cost of electricity ($/MWh)	0.14073
Location site (km)	0.23357
Capital cost ($)	0.18379

As shown on Table 3, efficiency has the highest priority weight and levelized cost of electricity has the lowest priority weight. These priority weights will then be incorporated into the energy cost model, which will be discussed in the next subchapter.

B. Energy Cost Model

The updated energy production model already has incorporated priority weights into it, which is shown in (10).

$$E = -0.44191A + 0.14073B + 0.23357C + 0.18379D \tag{10}$$

where A is efficiency (%), B is levelized cost of electricity ($/MWh), C is location site (km), and D is capital cost ($).

It is now important to determine the values of A, B, C, and D. Due to the different types of units that will be used in the energy consumption model, it is imperative that the values are 'standardized'. To do this, a logarithmic function will be used in each of the KPIs.

Because Indonesia did not yet have a nuclear power plant for generating energy for public demand, the data used are general data from trusted websites[1,2,3]. A range of values is used for each of the KPIs, and in the algorithm later, randomized values for each of the variables will be generated within that specific range. The data for the KPIs are on Table 4.

Table 4. Data for KPIs

KPIs	**Values**
Efficiency (%)	33 – 37
Levelized cost of electricity	39.39 – 126.37

[1] https://energyeducation.ca/encyclopedia/Nuclear_power_plant#:~:text=Typical%20nuclear%20power%20plants%20achieve,potentially%20reach%20above%2045%25%20efficiency.

[2] https://www.oecd-nea.org/upload/docs/application/pdf/2020-12/egc-2020_2020-12-09_18-26-46_781.pdf

[3] https://world-nuclear.org/information-library/economic-aspects/economics-of-nuclear-power.aspx

($/MWh)	
Location site (km)	8 – 30
Capital cost ($)	106 – 816

The energy cost model will then be utilized for the whale optimization algorithm, which will be discussed in the next subchapter.

C. Whale Optimization Algorithm

Fig. 9 shows the coding conducted to perform the whale optimization algorithm process.

```
# Required Libraries
import numpy as np
import random
import gc

# iWOA
from pyMetaheuristic.algorithm import improved_whale_optimization_algorithm
from pyMetaheuristic.utils import graphs

# Target Function - It can be any function that needs to be minimize, However it has to have only one argument: 'variables_values'. This Argument must be a list of variables.

# Target Function: Easom Function


def easom(variables_values = [0, 0, 0, 0]):
    A, B, C, D    = variables_values
    A = random.randrange(33, 37)
    B = random.randrange(40, 126)
    C = random.randrange(8, 30)
    D = random.randrange(106, 816)
    func_value = (-1*(0.44191 * (np.log(A)))) + (0.14073 * (np.log(B))) + (0.23357 * (np.log(C))) + (0.18379 * (np.log(D)))
    return func_value


# iWOA - Parameters
parameters = {
    'hunting_party': 500,
    'min_values': (33, 40, 8, 106),
    'max_values': (37, 126, 30, 816),
    'iterations': 1000,
    'spiral_param': 0.5,
    'mu': 3,
    'verbose': True
}

# iWOA - Algorithm
iwoa = improved_whale_optimization_algorithm(target_function = easom, **parameters)

# iWOA - Solution
variables = iwoa[0][:-1]
minimum   = iwoa[0][ -1]
print('Variables: ', np.around(variables, 4) , ' Minimum Value Found: ', round(minimum, 4) )


gc.collect()
```

Figure 9. Whale Optimization Algorithm Coding

Shown in Fig. 9, there are some parameters in the WOA algorithm that require explanations and/or clarifications:

- The minimum values set in the algorithm are based on the minimum values of the parameters' range of values. For example, the minimum value set for efficiency is 33%, since in the range of possible efficiency values, 33% is the lowest value.
- The maximum values follow the same logic as that of the minimum values; they are based on the maximum values of the parameters' range of values.
- There are 1000 iterations utilized. This is to ensure that the global optimum is found instead of local optima (1000 iterations are more than enough to find the global optimum).

The whale optimization algorithm deals with data that are randomly generated. Therefore, it is highly important that numerous trials are conducted to produce multiple objective function values that can be compared. The comparisons will determine the lowest objective function value, in which the best parameter values are contained.

To ensure that the results achieved reduce the extreme probabilities, 50 trials will be conducted. However, there are some trials that have equal objective values. They shown on Table 5.

Table 5. Objective Functions with Equal Value

Trials	**A**	**B**	**C**	**D**	**Objective**
1	37.00	41.86	30.00	137.5	0.2783
2	37.00	44.31	15.85	801.0	0.2783

3	37.00	126.0	24.1	816.0	0.2783
4	34.74	95.13	15.49	477.4	0.2783
5	33.00	40.00	8.000	106.0	0.2783

As there are five objective functions that have the lowest objective values that are equal, the values of the variables must now be considered. There cannot be multiple solutions; there can only be one. Therefore, two considerations are developed:

- The efficiency value must not be high.
- The costs' values must be low.

By looking at Table 5, it can be determined that the first objective function value is the best one. Therefore, the values to achieve the best solution are:

- Efficiency: 37%
- Levelized cost of electricity: $41.86/MWh
- Location site: 30 km
- Capital cost: $137.5

4. Conclusion

In conclusion, it can be gainsaid that the research is successful, in that it achieves the following three objectives:

- The KPIs for choosing the best clean energy source have been identified through consultation with experts within the energy field. The KPIs are also set as the parameters of the chosen clean energy source that must be optimized later.
- The decision-making process to choose the best clean energy source has been conducted successfully. AHP is used as the decision-making tool that proves to be sufficient to make decisions regarding this case.
- Python has been utilized for whale optimization algorithm application. The programming language has allowed good-quality results to be produced, which are then further processed to determine the optimized parameters.

There are, however, improvements to be made in this research. It is perhaps recommended that in the future, multiple optimization algorithms should be used instead of one, and the algorithm with the best result should be the one chosen. The second recommendation is that AHP should be integrated with another decision-making tool to produce better quality results (e.g., combining AHP with DEMATEL). Lastly, the research can be improved by conducting the research practically as well instead of just theoretically (this should be done with supervision from experts within the related field).

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