

Implementation of the Analytic Hierarchy Process (AHP) to Determine Key Performance Indicator (KPI) Weights for Steam Turbine Power Plant Using Python

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ABSTRACT

The optimization of Key Performance Indicators (KPIs) in steam turbine power plants is crucial for enhancing operational efficiency in the palm oil processing industry. This study applies the Analytic Hierarchy Process (AHP) to determine the relative weights of KPIs, thereby supporting data-driven decision making for performance improvement. Four critical KPIs were evaluated through pairwise comparisons expertise. A Python based computational model was developed to automate AHP calculations, ensuring accuracy and efficiency in deriving priority weights. This study reveals power output (47.16%) is the most significant KPI, followed by availability factor (38.58%), steam consumption (9.69%), and capacity factor (4.58%). The consistency ratio (CR) for all expert judgments was below 0.10, validating the reliability of the AHP outcomes. This research demonstrates that integrating AHP with Python programming provides a robust framework for KPI prioritization. The findings offer practical insights for industry stakeholders to optimize steam turbine performance and reduce operational inefficiencies.

KEYWORDS: AHP, KPIs, Steam Turbine, Python Programming, Decision-Making.

NOMENCLATURE

n	Number of criteria
CI	Consistency Index
μ_{max}	the biggest eigen value
RI	Random Consistency Index
CR	Consistency Ratio
W_j	Final Aggregated weights

1. INTRODUCTION

Power plant has become an essential requirement of CPO (Crude Palm Oil) processing manufacturing industry. To enhance operational efficiency, it is essential to identify and prioritize Key Performance Indicators (KPIs) that accurately reflect plant performance. However, determining the relative weights of these KPIs involves complex decision-making due to multiple competing criteria.

The Analytic Hierarchy Process (AHP) serves as an effective decision-making methodology for complex issues that involve multiple criteria or objective [1], [2]. AHP method provides a versatile approach for naturally inconsistent decision-making problems [3]. In the context of power plants, AHP has been used to develop weightings for Key Performance Indicators (KPIs), helping management make informed decisions for continuous improvement [4]. For instance, in biomass conversion technology selection, criteria such as technology maturity, conversion efficiency, and costs were ranked using AHP to identify the optimal choice for biofuel production in India [5]. By breaking down complex decisions into pairwise comparisons and combining the results, AHP provides a systematic approach to prioritizing factors and alternatives in decision-making processes. This study explores the application of AHP in evaluating KPIs for steam turbine power plants, leveraging Python to automate calculations and ensure consistency in the weighting process.

Emawan et. al. [4] carried out a study on the performance of a gas engine power plant. The study used a forum group discussion (FGD) to define the key performance indicators (KPIs) for a gas engine power plant. They applied the AHP to develop the weighting of the KPI criteria. The weighting of the KPI criteria was: Rank, Power Output (MW) at 70.81%, Rank 2, Heat Rate (Btu/kW) at 14.91%, Rank 3, Operating Ratio (%) at 8.06%, and Rank 4, Capacity Factor (%) at 6.22% [4].

Mufrida conducted the research to determining the priority of KPIs for measurement of hydro powerplant maintenance at Lubuk Gadang hydropower plant. The outcome of this research is most prioritized KPI for the Lubuk Gadang hydropower plant is the number of kW produced, with a weight of 0.420 at the corporate level. The most prioritized KPI at the strategic level is capacity factor, with a weight of 0.478. The most prioritized KPI at the functional level is rework maintenance, with a

weight of 0.540 [6]. These studies demonstrate that AHP has been effectively used in different power generation systems, such as gas and hydro power plants, to support decision-making in determining KPI priorities. Therefore, this study extends the application of AHP to a steam turbine power plant operating with biomass fuel in order to determine the most appropriate KPI weighting for performance evaluation.

This research aims to bridge that gap by developing a Python-based AHP model to determine KPI weights, thereby supporting data-driven decision-making for improved steam turbine power plant management. The findings are expected to contribute to both academic discourse and practical advancements in renewable energy performance assessment.

PT. KJA is a crude palm oil (CPO) processing company that operates a captive power plant to support its production activities. The power generation system consists of a Jabsen & Jessen Technology NG steam turbine with a capacity of 5500 kW, supplied by a Mackenzie Biomass boiler capable of producing 55 MT/hr of steam. This system utilizes biomass fuel derived from Palm Kernel Shell to generate electricity for internal plant operations.

1.1 Utility and Power Plant Process Plant

The utility and power plant are two interrelated units that serve as support system for production plant in palm oil refining and oleo-chemical processing industries. In general, the following Figure 1 is the flow process of the utility and power plant system commonly found in refinery and oleo-chemical industry.

In the Figure 1, the process of steam and electricity generations begin with the intake of water from Water Treatment Plant (WTP), ensuring that the water quality meets the required specification. The water is first stored in water tank (T103), which, acts as a temporary holding reservoir for water transferred from WTP. The water is then pumped into the deaerator unit using deaerator pump. The deaerator is water treatment unit that functions as oxygen scavenger, where the temperature must be maintained between 101 °C to 105°C [7]. The oxygen content present in the water can lead the damage in the pipes within the boiler system. This damage is evident through corrosion and pipe leakage. The next process involves transferring the water, which has been deoxygenated in the

deaerator system, to the steam drum boiler using feed water pump. In the steam drum, the phase change of water into steam occurs. The heating of water within steam drum is achieved through the combustion of fuel in the furnace, with temperatures ranging from 850°C to 950°C. The operating pressure within each boiler varies, depending on specific operational requirements of the plant [8].

Subsequently, the steam produced in the steam drum is directed to the super-heater tube system, where it undergoes reheating to achieve a dry steam state. The configuration and capacity of the super-heater system depend on the specific requirements of the power plant. After passing through the super-heater, the steam is delivered to the turbine to generate both electrical and thermal energy. The electricity and steam produced are then utilized in various production processes. The turbine system is also supported by a cooling tower, which functions as a cooling medium for both the condenser and the generator. The production of steam and electricity is also have excess steam and condensate water, generated through the condensation process within the system. This condensate is processed in the condenser unit to facilitate its conversion back into water, which is then transferred to the water storage tank (T103). This entire cycle is continuous and operates in a closed-loop system to ensure sustainability and resource efficiency.

Boiler can operate using a diverse range of fuel sources, including production process residues, steam turbine-derived feedstock, coal refuse, natural gas, diesel oil and other combustible materials, depending on availability and operational requirements [9].

1.2 Key Performance Indicators (KPIs) in Power Plant

The primary purpose of evaluating and monitoring key performance indicators (KPIs) in power plant operations is to identify areas of underperformance, analyze underlying problems, and develop maintenance strategies aimed at reducing operational costs [10]. The main objectives of assessing the technical performance of power plants based on renewable sources are monitoring the operation of generating units or groups, identifying decline in their performance and also the need to perform maintenance/repairs on the affected groups.

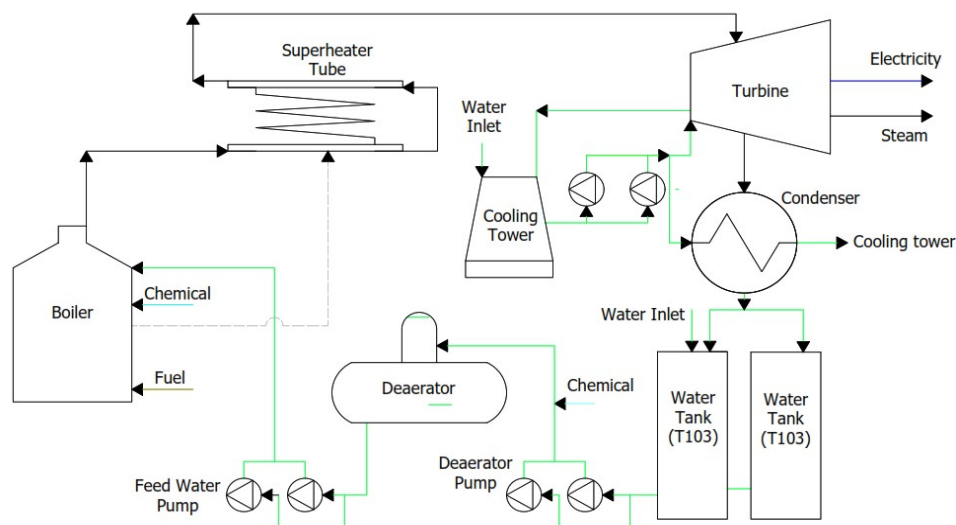


Figure 1: Utility and power plant process flow diagram PT. KJX

Commissioning, recommissioning or evaluation after repairs, benchmarks for measuring and comparing further performance, calculating specific parameters such as yield, performance ratio to enable comparisons between power plants operation in different geographical areas and assisting decisions regarding investment in new groups or extending existing ones [10].

Technical performance indicators according to Emawan [11] based on operational data consist of the Average Power (PAvg), installed power load factor (Ku); installed power load duration (Ti), maximum power load duration (Tmax), power factor (Cos θ), performance index (PI) [4]. The performance of a coal-fired power plant (CFPP) is considered efficient when analysed based on three main parameters: boiler efficiency (based on LHV), heat rate (based on HHV), and thermal efficiency [11].

1.3 Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process is a decision-making approach designed to address problems from both rational and intuitive aspects. It helps in selecting the best alternative from a set of options to be evaluated based on several criteria that are taken into consideration [1]. In Figure 2, the simplest form of structuring a decision-making process for a problem is a hierarchy consisting of three levels: the first level is the goal or decision objective at the top, followed by the second level which includes the criteria used to evaluate alternatives that are located at the third level. The deconstruction of the hierarchy in a complex system is a fundamental tool used by the human mind to address diversity. A person organizes the factors influencing a decision step by step, starting from the general at the top level of the hierarchy down to the specific at the lower level. The purpose of this structure is to enable us to assess how important the elements at a given level are compared to several or all of the elements at the level above it [1].

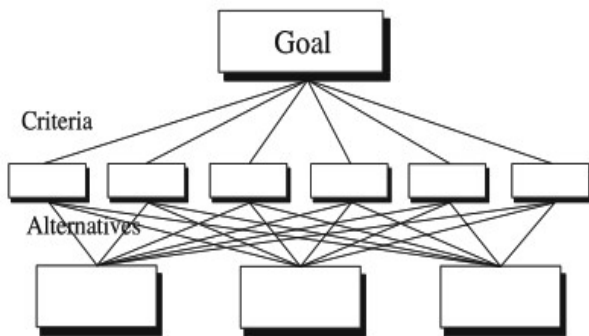


Figure 2: Three level hierarchy of AHP

Pairwise comparison assessments in the AHP are conducted between pairs of homogeneous elements [12]. A fundamental value scale is employed to quantify the judgments of decision makers throughout the pairwise comparison process. The validity of this scale should be established not only through its consistent application across diverse decision makers, but also through a sound theoretical foundation that justifies its use in comparing homogeneous elements. The fundamental scale of the AHP presents in Table 1.

Table 1: The fundamental scale of AHP

Intensity of importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak Moderate importance	Experience and judgment slightly favour one activity over another
3		
4	Moderate plus Strong importance	Experience and judgment strongly favour one activity over another
5		
6	Strong plus Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
7		
8	Very, very strong Extreme Importance	The evidence favouring one activity over another is of the highest possible order of affirmation
9		
Reciprocals of above	If activity i has one of the above non zero number assigned to it when compare with activity j, then j has the reciprocal value when compared	A reasonable assumption
Rational	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

The eigenvector solution is essential in deriving the priority vector, or weights, from the pairwise comparison matrix. To ensure consistency in judgments, the concept of the principal eigenvalue is introduced, expressed by the equation $Aw = nW$, where A represents the pairwise comparison matrix, $w = (w_1, w_2, \dots, w_n)$ denotes the weight vector to be determined, and n is the principal eigenvalue, functioning as a scaling factor. The ratio comparison matrix is then constructed and multiplied by the weight vector on the right-hand side to yield $n \cdot w$, as shown in the following expression:

$$\begin{pmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_2} & \frac{w_2}{w_2} & \dots & \frac{w_2}{w_n} \\ \frac{w_3}{w_3} & \frac{w_3}{w_2} & \dots & \frac{w_3}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & \frac{w_n}{w_n} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = n \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} \quad (1)$$

In the Analytic Hierarchy Process (AHP), the eigenvalue is used to evaluate the consistency of the pairwise comparison matrix. After obtaining the priority weight vector, the maximum eigenvalue (λ_{max}) is calculated to measure the consistency level of the judgments provided by the experts.

The value of (λ_{max}) is obtained by multiplying the pairwise comparison matrix A with the priority vector w and then dividing each resulting element by the corresponding weight value. The average of these values represents the maximum eigenvalue.

$$A \cdot w = \mu_{max} \cdot w \quad (2)$$

The maximum eigen-vector is calculated according to the Equation 3

$$\mu_{max} = \frac{1}{n} \sum_{i=j}^n \frac{(A_w)}{(W_j)} \quad (3)$$

The formula for consistency index (CI) calculation is

$$CI = \frac{(\mu_{max} - n)}{(n - 1)} \quad (4)$$

The formula for consistency ratio (CR) is

$$CR = \frac{CI}{RI} \quad (5)$$

The Random Index (RI) is a reference value used to measure the consistency of pairwise comparisons in AHP. The RI values were developed by Saaty based on randomly generated matrices and vary depending on the number of criteria used in the comparison matrix. In this study, the RI value corresponding to the number of criteria was used to calculate the Consistency Ratio (CR), where a CR value less than 0.1 indicate acceptable consistency.

The consistency ratio (C.R.) is obtained by comparing the C.I. with the appropriate one of the following set of numbers (see Table 2). Each of which is an average random consistency index derived from a sample of randomly generated reciprocal matrices using the scale 1/9, 1/8, ..., 1, ..., 8, 9.

Table 2: Random consistency index (R.I)

N	1	2	3	4	5	6	7	8	9	10
(R.I)	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

If it is not less than 0.10, study the problem and revise the judgments. The AHP includes a consistency index for an entire hierarchy. An inconsistency of 10 percent or less implies that the adjustment is small compared to the actual values of the eigenvector entries.

The relative weights of the criteria are combined to produce a unified weight that reflects a group decision, aiming to reduce disagreements among individuals with differing preferences. This is done using an aggregation method based on geometric means to compute overall scores for the group. When

individuals assess different subsets of criteria, the suggested approach proposed by involves converting individual rankings into weights, which are then averaged to derive the final aggregated weights [13]. The results of the study show that the geometric means aggregation method is superior to the geometric means method due to its ability to reflect preference information and avoid rank reversal [14]. The equation, where m is the number of individuals, is in Equation 5.

$$W_j = \sqrt[m]{W_{1j} \times W_{2j} \times \dots \times W_{mj}} ; j = 1, \dots, n \quad (6)$$

1.4 Computational Implementation of AHP Using Python

Python offers several advantages over Excel in data processing and analysis. While Excel often requires multiple manual steps for tasks such as data import, filtering, duplicate detection, format conversion, and dataset merging, Python can perform these operations automatically through scripts. With libraries such as Pandas and NumPy, Python enables faster processing, efficient handling of large datasets, and flexible data manipulation. Therefore, Python provides a more scalable, efficient, and reliable approach for data analysis compared to Excel [15], [16]. Therefore, Python offers a more scalable and reliable approach for implementing AHP in evaluating and determining Key Performance Indicator (KPI) weights for steam turbine power plant performance.

The theoretical framework of AHP relies heavily on matrix algebra and iterative calculations, which can be tedious and error-prone when performed manually. Computational tools like Python streamline this process by automating complex mathematical operations, ensuring accuracy, scalability, and reproducibility. Python's open-source ecosystem, coupled with its robust scientific libraries, makes it an ideal platform for implementing AHP, particularly in multi-criteria decision-making (MCDM) problems such as KPI weighting for steam turbine power plants.

Implementing AHP steps by hand can be tedious, especially for group judgments. Modern computing eases this: for example, NumPy (a Python library) can represent pairwise comparison matrices as arrays and compute eigenvalues/vectors using `numpy.linalg.eig()`. Matplotlib (another Python library) can plot bar charts of the resulting 4 weights for clear interpretation. Automating AHP in Python ensures rapid, reproducible analysis and straightforward consistency checks. In this work, a Python program was developed to implement the full AHP workflow: inputting expert comparisons, computing weights, verifying CR, aggregating opinions, and visualizing final priorities. This computational approach leverages open-source tools to support data-driven decision making in power plant management.

NumPy is a fundamental library for scientific computing in Python that provides efficient multidimensional array structures and mathematical operations. In this study, NumPy was used to perform matrix operations required in the AHP, particularly for calculating eigenvectors and eigenvalues from the pairwise comparison matrix to determine the priority weights of the KPIs [17]. The resulting eigenvector represents the priority weight of each KPI used in the decision-making process. Matplotlib is a Python library used for creating graphical visualizations. In this study, it was utilized to present the calculated KPI weights and analysis results in graphical form to support clearer interpretation of the AHP outcomes [18].

```
>>> a = np.arange(6) # 1d array
>>> print(a)
[0 1 2 3 4 5]
>>>
>>> b = np.arange(12).reshape(4,3) # 2d array
>>> print(b)
[[ 0 1 2]
 [ 3 4 5]
 [ 6 7 8]
 [ 9 10 11]]
>>>
>>> c = np.arange(24).reshape(2,3,4) # 3d array
>>> print(c)
[[[ 0 1 2 3]
 [ 4 5 6 7]
 [ 8 9 10 11]]
 [[12 13 14 15]
 [16 17 18 19]
 [20 21 22 23]]]
```

Figure 3: NumPy example print out

If matplotlib were limited to working with lists, it would be fairly useless for numeric processing. Generally, you will use numpy arrays. In fact, all sequences are converted to numpy arrays internally. The example below illustrates a plotting several lines with different format styles in one command using arrays:

```
import numpy as np
import matplotlib.pyplot as plt
# evenly sampled time at 200ms intervals
t = np.arange(0., 5., 0.2)
# red dashes, blue squares and green triangles
plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
plt.show()
```

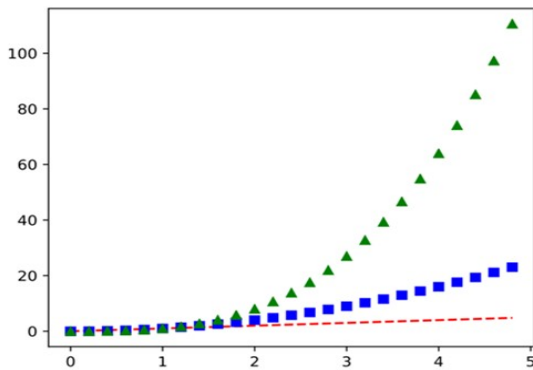


Figure 4: Matplotlib example

2. METHODS

2.1 Analytic Hierarchy Process (AHP) Methodology

The Analytic Hierarchy Process (AHP) is employed in this study to evaluate the Key Performance Indicators (KPIs) of a steam turbine power plant. The AHP methodology is implemented through the following structured steps:

1. Problem definition and goal setting. The primary objective of this study is to assess and prioritize the KPIs of a steam turbine boiler steam turbine system. This goal is established as the top level (Level 1) of the hierarchical structure.

2. Hierarchical structure development. A two-level hierarchy is constructed to systematically evaluate the KPIs:
 - Level 1 (Goal): Key Performance Indicator (KPI) Weights for Steam Turbine.
 - Level 2 (Criteria): The selected criteria, derived from a literature review, include:
 - Total power output (kW)
 - Availability Factor (%)
 - Steam consumption (kg/kWh)
 - Capacity factor (%)

This structured AHP approach ensures a systematic and objective evaluation of KPIs, supported by expert judgments and quantitative analysis. Figure 5 presents all step workflow of AHP methodology.
3. Pairwise comparison matrix. For each hierarchical level, pairwise comparison matrices are constructed by evaluating the relative importance of elements using Saaty's 1-9 scale, where 1 indicates equal importance and 9 signifies extreme importance of one element over another.
4. Normalization and priority vector calculation. Each pairwise comparison matrix is normalized by:
 - Summing the values in each column,
 - Dividing each element by its respective column total, and
 - Calculating the row averages to derive the priority vector (relative weights).
5. Consistency Ratio (CR) verification. The consistency of each pairwise comparison is assessed by computing the Consistency Ratio (CR). A CR value below 0.10 indicates acceptable consistency in judgments; otherwise, the comparisons are revised.
6. Result synthesis. The relative weights of criteria and alternatives are aggregated across the hierarchy to determine the overall priority scores for each KPI alternative.
7. Decision making. The alternative with the highest overall score is identified as the optimal choice, providing a data-driven recommendation for KPI prioritization in steam turbine boiler steam turbine operations.

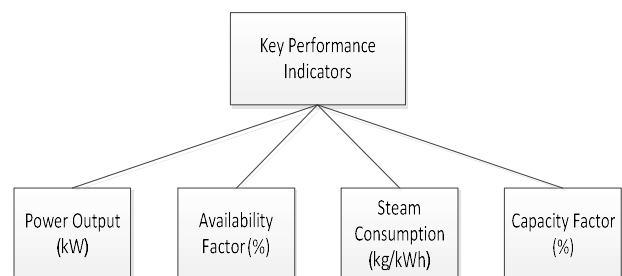


Figure 5: Hierarchy Structure

2.2 Python Computational AHP Flow

Python can assist decision makers in structuring goals and defining criteria, calculating the pairwise comparison matrix, performing normalization, deriving eigenvectors to obtain priority vectors, and computing the Consistency Index (CI), Consistency Ratio (CR), and final results. The development of an appropriate python programming requires a systematically designed algorithm as a foundational basis for its

implementation in Python. Figure 6 presents the algorithmic workflow of the Analytic Hierarchy Process (AHP), which is executed using Python programming.

Using NumPy, pairwise comparison matrix as a 2D array can be created, then calculate the priority weights by finding the principal eigenvector from the matrix's eigenvalues and eigenvectors. Normalize this eigenvector to sum to one for the weights. Next, calculate the Consistency Index (CI), where

λ_{max} is the largest eigenvalue and n is the matrix size, then use a Random Index (RI) lookup to compute the Consistency Ratio to check matrix consistency ($CR < 0.1$ means acceptable). Finally, visualize the weights with matplotlib by plotting a bar chart with KPI labels on the x-axis and normalized weights on the y-axis for clear interpretation of relative importance.

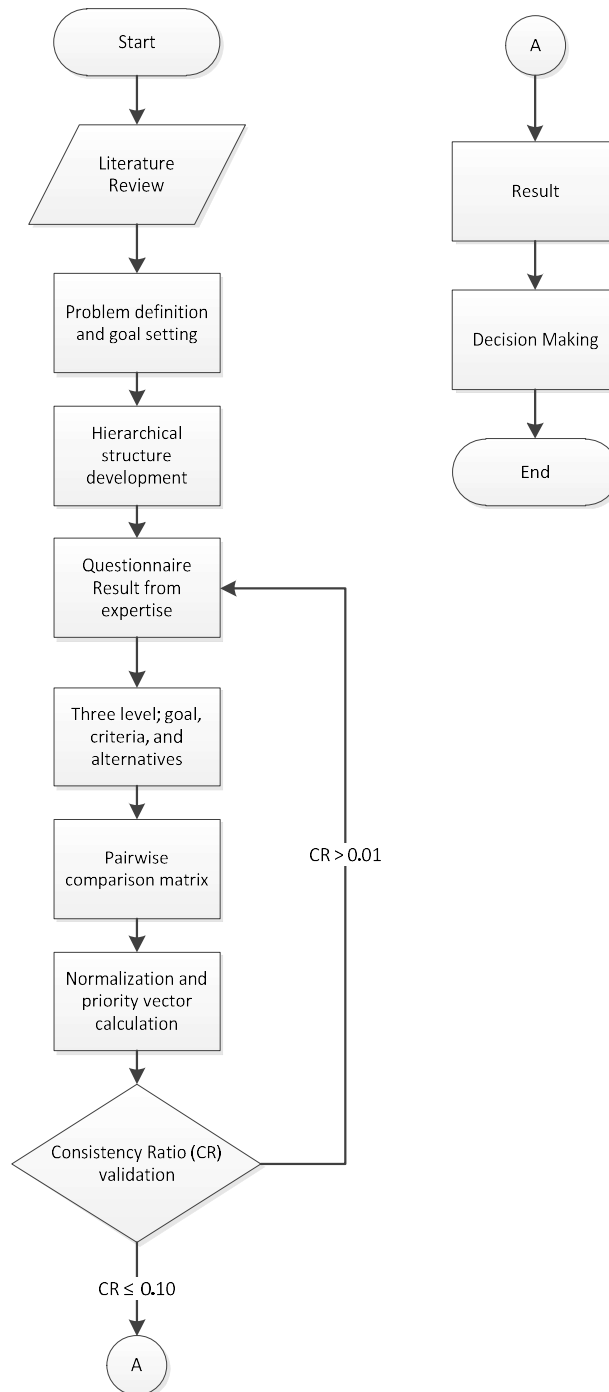


Figure 6: Flow Chart AHP Methodology

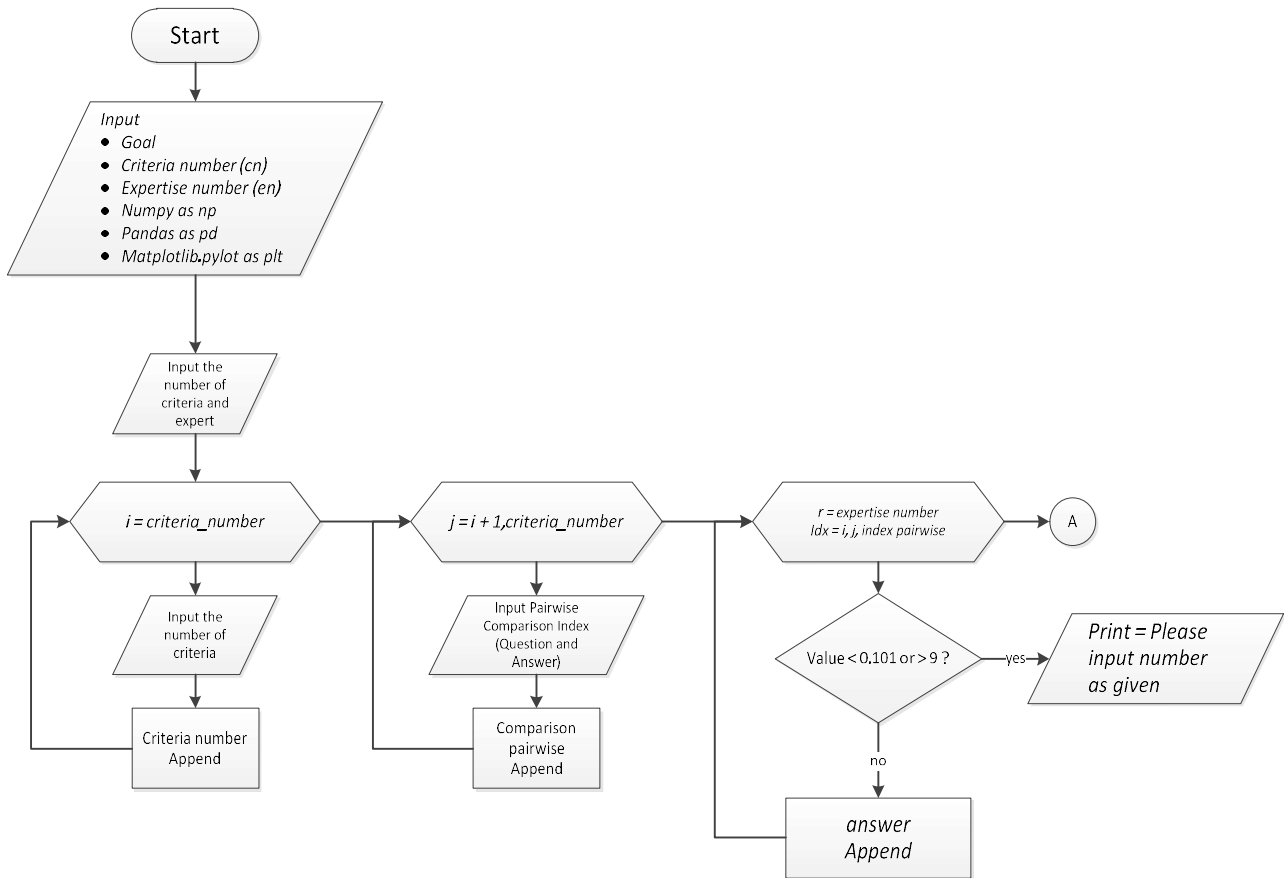


Figure 7: Algorithms of python (questionnaires)

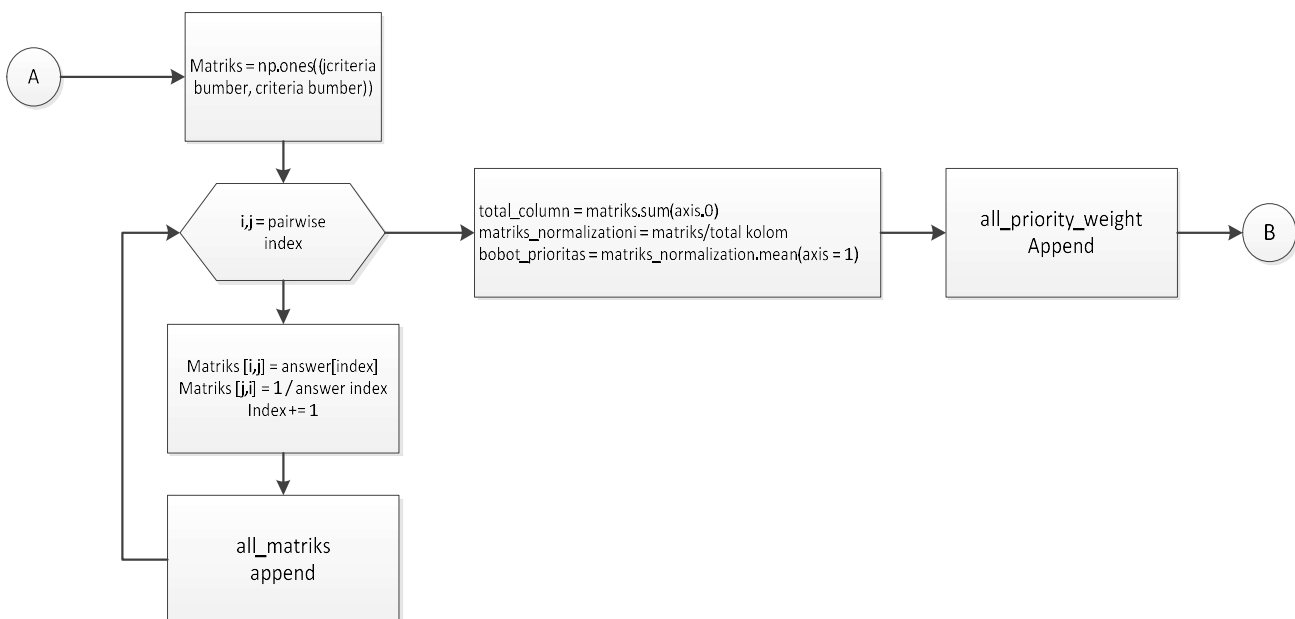


Figure 8: Algorithms of python (Matriks calculations, normalised and weights priority)

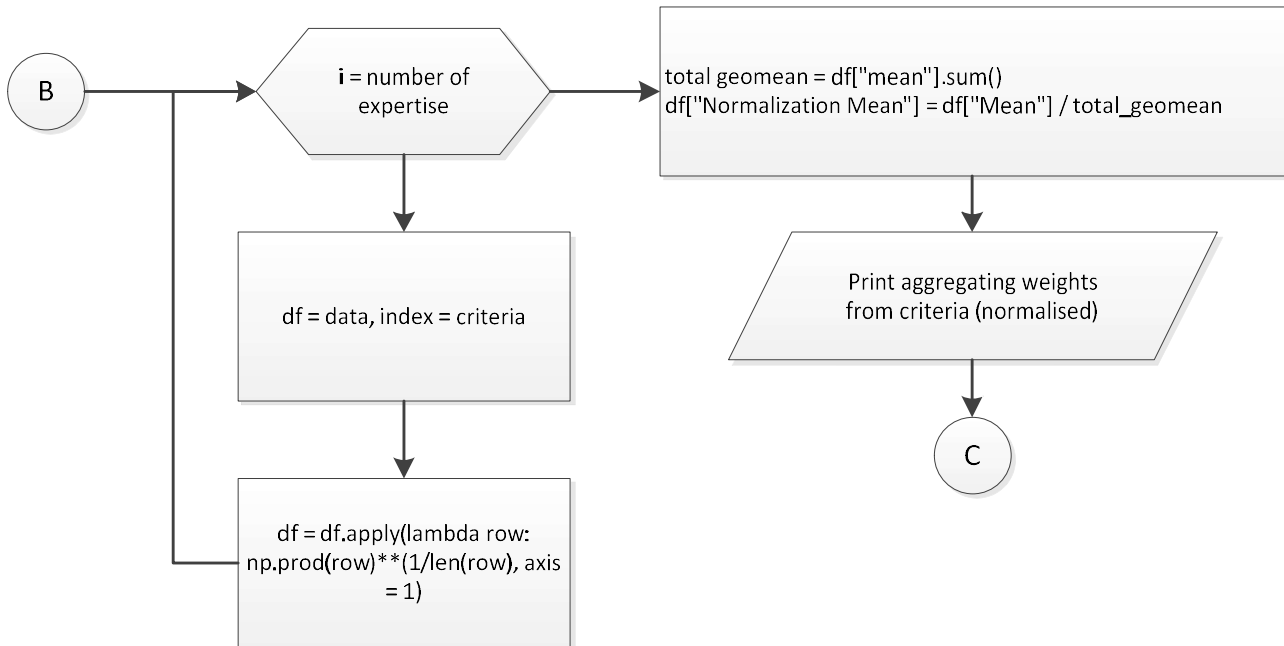


Figure 9: Algorithms of python (Aggregation Weights with Geometric mean Calculation)

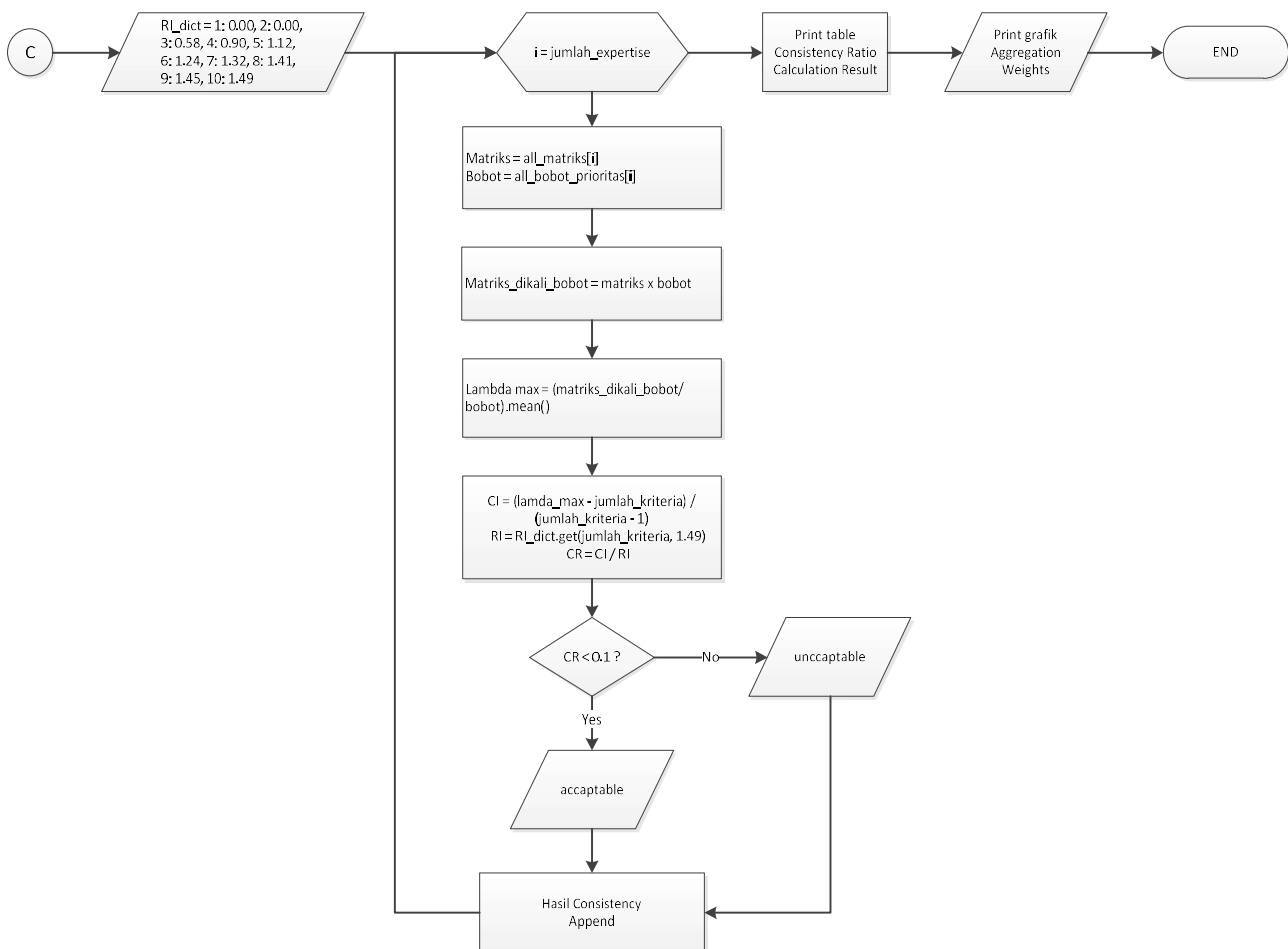


Figure 10: Algorithms of python (CR, CI, λ max calculation and graphic print)

In this study, the Python code was developed to support the analysis and implementation of the proposed methodology. The script was designed to process the relevant data, perform the necessary computations, and generate the results used for further interpretation. The code plays a critical role in ensuring the accuracy and reproducibility of the research findings.

3. RESULT AND DISCUSSION

3.1 Define the KPIs of Steam turbine

To evaluate the performance of steam turbine power plants, several key performance indicators (KPIs) are commonly used. These KPIs described as follow:

1. Total power output (kW)

Refers to average total electrical power generated by turbine, measured in kilowatts (kW). It represents the plant's overall production capability over a specific period.

2. Availability factor (%)

Percentage of time the plant is available to generate power (whether or not it's actually generating).

3. Steam consumption (kg/kW)

Steam consumption is amounting steam required by turbine to produce one kilowatts-hour of electricity generated. The energy input is measured in kilo-joule. Lower steam consumption ratio indicated better processing cost.

4. Capacity factor (%)

Capacity factor is the ratio of actual electricity energy produced over a given to the maximum possible energy that could have been produced if the plant operated at full capacity continuously. It shows how effectively the installed generation is being utilized.

3.2 Analytic Hierarchy Process (AHP)

The weighting values of KPI are derived from the AHP calculation based on the respondent. All respondents are experts within the company. The questionnaire method is used to get answers from expertise, which is designed to obtain weighting of KPI. This questionnaire will be distributed to a senior supervisor who have more than 11 years of experience working in steam turbine power plants, and 2 Power plant and utility Engineer.

This questionnaire talks about the information from the respondents, namely the expertise in the company (name, gender, designation, how long experienced face to steam turbine power plant), department, and the relative importance of each criterion. This questionnaire design was then made by Python so that it is easy to distribute and receive responses from experts and to make it easy to calculate all those data related to KPIs. The table 3 represent that there is 3 expertise who give the answer to the questionnaire given. The intensity of importance for each KPI has also been given.

The next step involves calculating the Consistency Index (CI) using Equation (4). Once the CI for each expert is obtained, the Consistency Ratio (CR) is computed using Equation (5). The Random Consistency Index (RI) is determined based on the number of criteria (n). In this case, since $n = 4$, the corresponding RI value is 0.89, as referenced in Table 2. The consistency of the pair-wise comparison matrix is considered acceptable if the resulting CR is $\leq 10\%$.

Table 3: Questionnaire to respondent summary

	1	2	3
Position	Engineer	Engineer	Sr. SPV
Name	AA	AR	DS
Gender	Male	Male	Male
How long you have been working for power plant?	06 - 10 years	11 - 15 years	11 - 15 years
How much more important is Power Output (kW) compared to Availability factor (%)?	Power Output	Power Output	Availability factor
Power Output - Availability Factor	3	3	3
How much more important is Power Output (kW) compared to Steam consumption ratio (kg/kW)?	Power Output	Power Output	Power Output
Power Output - Steam Consumption	8	7	5
How much more important is Power Output (kW) compared to Capacity factor (%)?	Power Output	Power Output	Power Output
Power Output - Steam Capacity factor	9	7	7
How much more important is Availability factor (%) compared to Steam consumption ratio (kg/kW)?	Availability factor	Availability factor	Availability factor
Availability factor - Steam Consumption	6	4	6
How much more important is Availability factor (%) compared to Capacity factor (%)?	Availability factor	Availability factor	Availability factor
Availability factor - Capacity factor	9	8	9
How much more important is Steam consumption ratio (kg/kW) compared to Capacity factor (%)?	Steam consumption	Steam consumption	Steam consumption
Steam consumption - Capacity factor	3	3	4

However, if the CR exceeds 10%, the subjective judgments must be revised to ensure reliability. The CR calculations are summarized in Figure 11. This structured approach ensures the validity of the analytical process, aligning with established methodological standards in decision-making analysis.

```

===== Consistency Ratio Calculation Result =====
Expertise Lambda Max CI RI CR Status
Expertise 1 4.2158 0.0719 0.9 0.0799 Acceptable
Expertise 2 4.2071 0.0690 0.9 0.0767 Acceptable
Expertise 3 4.2393 0.0798 0.9 0.0886 Acceptable
    
```

Figure 11: Consistency ratio calculation result (Generated by Python)

The next step involves determining the weight for each criterion by aggregating the relative weights assigned by each expert. This aggregation is performed using the geometric mean method as described in Equation 5, which entails calculating the fourth root (corresponding to the number of criteria) of the product of the weights provided by the experts. After computing the geometric mean for each criterion, the normalized geometric mean is obtained by dividing each criterion's geometric mean by the sum of all geometric means. The results of this aggregation process are summarized in figure 12, which presents the final aggregated weights of the criteria, and the ranking can be seen in Figure 13.

```

===== Aggregating Weights From Criteria (Normalized) =====
Expertise 1 Expertise 2 Expertise 3 Rata-rata Rata-rata Normalisasi
Power Output 0.5673 0.5598 0.2946 0.4540 0.4716
Availability Factor 0.3116 0.2950 0.5575 0.3714 0.3858
Steam Consumption 0.0800 0.0961 0.1054 0.0932 0.0969
Capacity Factor 0.0410 0.0491 0.0425 0.0441 0.0458
    
```

Figure 12: Aggregating Weights from Criteria (Generated by Python)

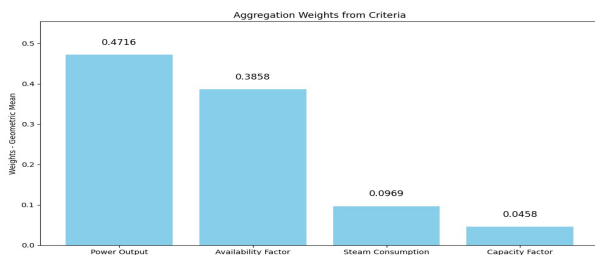


Figure 13: Aggregation weights from criteria ranking (generated by Python)

Based on the graph, it can be observed that the power output holds the highest priority weight at 47.16%, followed by the availability factor at 38.58%, steam consumption at 9.69%, and the capacity factor at 4.58%.

Previous studies have applied the Analytic Hierarchy Process (AHP) to determine the priority of Key Performance Indicators (KPIs) in various power generation systems. Emawan analyzed the performance of a gas engine power plant using Focus Group Discussion (FGD) to define KPIs and applied AHP to determine their weights. The results indicated that power output (MW) had the highest priority at 70.81%, followed by heat rate (14.91%), operating ratio (8.06%), and capacity factor (6.22%) [4]. Similarly, Mufrida investigated KPI prioritization for maintenance performance at the Lubuk Gadang hydropower plant. The study found that the number of kW produced was the most important KPI at the corporate level (0.420), while capacity factor (0.478) and rework maintenance (0.540) were the most prioritized KPIs at

the strategic and functional levels, respectively [6].

In comparison, the findings of this study show that power output remains the most important KPI, with a priority weight of 47.16%, indicating its critical role in evaluating steam turbine performance. This is followed by the availability factor (38.58%), steam consumption (9.69%), and capacity factor (4.58%). These results are generally consistent with previous studies, where power generation output tends to be the primary performance indicator in power plants, although the weighting distribution differs due to variations in power plant type, operational objectives, and evaluation criteria.

4. CONCLUSION

The findings of this study confirm that the Analytic Hierarchy Process (AHP) is a robust and effective method for determining the weights of key performance indicators in steam turbine power plants. The key performance indicators for steam turbines, in descending order of priority, are as follows: power output holds the highest priority weight at 47.16%, followed by the availability factor at 38.58%, steam consumption at 9.69%, and the capacity factor at 4.58%. Moreover, the use of Python as a computational tool for performing AHP calculations facilitates the decision-making process by enhancing computational efficiency and substantially reducing the time required for analysis.

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