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Decision Support Model for Determining Fuel in Boiler Machines

Jeremia Widyanto[1,*], Ditdit Nugeraha Utama[2,]

[1,2]Computer Science Department-BINUS Graduate Program-Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia

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Abstract

This investigation seeks to formulate a Decision Support Model (DSM) aimed at identifying the most suitable fuel for boiler systems utilized in industrial contexts, encompassing three distinct fuel categories: natural gas, industrial diesel oil, and coal. The assessment is predicated on four fundamental criteria: cost, calorific value, safety, and emissions. Employing a synergistic methodology that combines Analytic Hierarchy Process (AHP) and Fuzzy Logic, AHP allocates weights to each criterion (cost: 0.503, calorific value: 0.273, safety: 0.145, emissions: 0.079). The Fuzzy Logic approach is utilized to effectively address uncertainty and process subjective assessments. The findings indicate that cost constitutes the paramount determinant, exhibiting the highest weight, succeeded by calorific value, safety, and emissions. In accordance with these weighted criteria, the fuels are ordered as follows: coal (0.794), natural gas (0.653), and industrial diesel oil (0.456). These results underscore that cost remains the predominant factor in fuel selection for industrial boilers, whilst safety and environmental ramifications concurrently exert significant influence. The originality of this inquiry is manifested in its implementation of an all-encompassing DSM for fuel selection, marking a pioneering effort within this domain, which integrates both AHP and Fuzzy Logic to furnish a versatile and resilient decision-making framework. The implications of this research are substantial, as it offers a transparent and systematic approach for fuel selection in industrial environments, providing valuable insights into the optimization of energy resources while taking into account economic, environmental, and safety considerations. Subsequent investigations could further examine the incorporation of renewable energy sources and the ramifications of advancing environmental policies on fuel selection.

Keywords: Boiler Fuel, DSM, AHP, Fuzzy Logic, Emissions, Costs

1. Introduction

Boilers are essential components in various industrial sectors that rely on steam as a critical element in their production processes, including manufacturing, energy, and chemical industries. As a primary source of thermal energy, boilers convert the chemical energy of fuels into heat, which is then used to raise water to steam [1]. The selection of an appropriate fuel is crucial not only for optimizing operational efficiency but also for controlling costs, ensuring safety, and minimizing the environmental impact of boiler systems [2]. Fossil fuels, such as natural gas, diesel, and coal, are commonly used in industrial boiler applications due to their high energy efficiency. However, the combustion of these fuels leads to the emission of significant quantities of greenhouse gases (GHGs), including carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NOx), which contribute to global warming and air pollution [3].

Traditionally, fuel selection decisions for boiler systems have been made primarily based on two factors: fuel availability and cost [4]. However, as global awareness of environmental concerns grows, there is an increasing emphasis on incorporating other important criteria, such as carbon emissions, fuel safety, and calorific value, into the decision-making process [5]. Selecting the right fuel can lead to cost reductions, as well as contribute to sustainability efforts by reducing the environmental impact of energy production. This highlights the need for a more systematic approach to fuel selection—one that integrates both economic and environmental considerations [6].

A DSM offers a promising solution to address these complex multi-criteria decision-making problem [7]. The AHP is a well-established multi-criteria decision-making method that organizes complex, unstructured decisions into a simpler hierarchical structure [8]. The AHP process typically involves three main stages: hierarchy creation, pairwise comparison, and decision synthesis. In the first stage, decision objectives, criteria, and alternatives are organized

*Corresponding author: Jeremia Widyanto (jeremia.widyanto@binus.ac.id)
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hierarchically. In the second stage, pairwise comparisons are conducted using numerical ratings (values ranging from 1 to 9), which reflect the relative importance of each criterion. These comparisons are inherently subjective, as they are based on the expert's judgment, yet they are crucial for determining the relative weights of the decision criteria. The final stage involves synthesizing these comparisons to generate a ranking of the alternatives [9].

In this context, Fuzzy Logic is used to manage the uncertainty and subjectivity that arises in evaluating fuel selection criteria. Not all decision parameters can be assessed with precise numeric values, as many involve vague or imprecise information [10]. Fuzzy Logic allows for the representation of such criteria using membership values that range from 0 to 1. This approach can handle the inherent uncertainty in evaluating factors like safety and environmental impact. The Fuzzy Logic process consists of three stages: fuzzification, inference, and defuzzification. In the fuzzification stage, crisp numerical inputs are converted into fuzzy values representing degrees of membership in fuzzy sets. In the inference stage, IF-THEN rules are applied to relate fuzzy inputs to fuzzy outputs. Finally, in the defuzzification stage, the fuzzy results are converted back into precise numerical values using methods such as the Centroid technique, which calculates the center of gravity of the fuzzy set [11].

This study aims to develop a comprehensive DSM that can assist in recommending the optimal fuel for industrial boilers by evaluating and comparing fossil fuels—such as natural gas, diesel, and coal—based on both economic and environmental parameters [12]. By integrating AHP and Fuzzy Logic, this model provides a flexible and robust approach to fuel selection that considers both cost-efficiency and environmental sustainability [13]. The application of this DSM model is expected to offer valuable insights for industries seeking to optimize their fuel selection process, contributing to both economic savings and environmental goals [14]. Furthermore, the integration of these decision-making techniques aligns with current trends toward sustainable industrial practices and carbon footprint reduction [15].

2. Method

2.1. DSM

This study develops a DSM to select the optimal fuel in a boiler engine, using a combination of AHP and Fuzzy Logic approaches [16]. This section describes in detail the research methods applied, including data collection, model design, and evaluation stages, as shown in figure 1.

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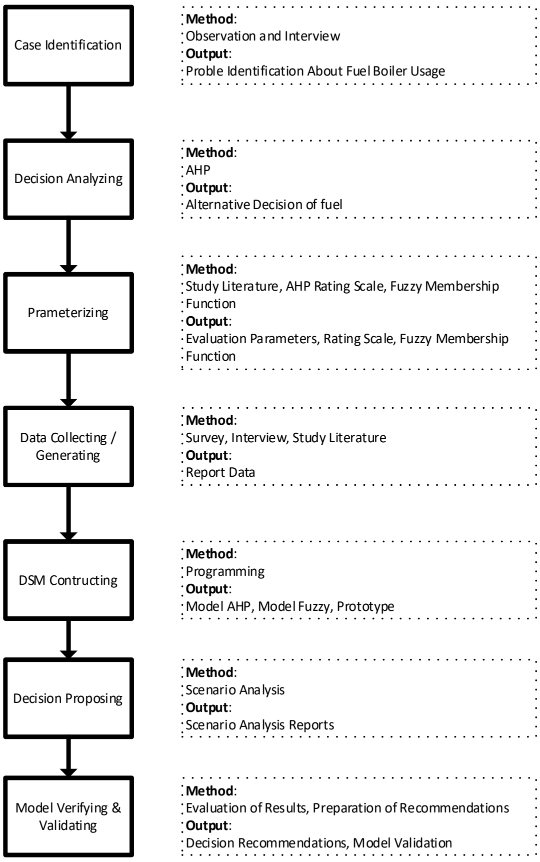

Figure 1. DSM Method

The investigation begins with identifying the case, where current methods for determining fuel in boiler systems are examined. Many companies still rely on manual methods for choosing fuel, and sometimes there is no organized system or model in place. To understand these methods, real data is collected directly from industries using boilers through site visits, discussions with boiler operators, and meetings with industry experts [17]. The next step, decision analysis, involves evaluating different fuel options based on the set criteria. Key stakeholders involved in the decision-making process are identified, and a decision hierarchy is created using the AHP, which includes main objectives, criteria, sub-criteria, and fuel options [18]. After this, during the parameterization stage, the relevant parameters for fuel selection are outlined based on the results of the decision analysis. These parameters—cost, calorific value, safety, and emissions—are validated through relevant research and expert interviews. The parameters are then combined to create a basis for building a model [19]. In the data collection phase, necessary data for each identified parameter is gathered from both secondary sources (like academic literature and industry reports) and primary sources (through surveys and interviews). When data limitations arise, data construction techniques are used to generate needed data for later calculations [20]. Finally, in the DSM construction phase, the gathered data is used to create a complete DSM for fuel selection in boilers. The model combines AHP and Fuzzy Logic to address multi-criteria decision-making, where AHP assigns weights to criteria, and Fuzzy Logic manages uncertainty and subjectivity in assessment. This combination of methods supports a flexible, clear, and realistic decision-making process for fuel selection in industrial boiler systems [21].

The process of integrating AHP and Fuzzy Logic for selecting the optimal fuel for industrial boilers involves several stages, focusing on key factors such as cost, calorific value, safety, and emissions [22]. The first step is identifying the main criteria based on a review of literature and expert opinions. These criteria are then analyzed to determine their importance, with AHP being used to assign weights to each factor [23]. AHP creates a hierarchical structure to compare the criteria and determine their relative importance through pairwise comparisons. This results in a set of weights that guide the decision-making process. However, fuel selection often involves uncertainty, especially when evaluating subjective factors like safety or emissions [24]. To address this, Fuzzy Logic is applied. It allows the evaluation of each

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criterion using fuzzy values (e.g., "Not Tight" to "Tight" for safety), which better reflects the complexities of real-world decisions. These fuzzy values are then converted into clear, actionable numbers through defuzzification [25]. Finally, the results from both AHP and Fuzzy Logic are combined. The fuzzy evaluations for each fuel are multiplied by the AHP-derived weights, resulting in an overall score for each fuel. This integrated approach provides a more accurate and comprehensive fuel selection process, accounting for both the relative importance of each criterion and the uncertainties in the evaluation [26].

2.2. Decision Proposing

In this phase, the DSM is used to assess different fuel selection scenarios, based on the criteria and parameters set earlier in the study [27]. The model is meant to handle various fuel types—like natural gas, diesel, and coal—while factoring in a range of important evaluation aspects, such as cost, energy content, safety, and emissions [28]. Each scenario is tested to see how different fuel mixes satisfy the established criteria under diverse operational situations. The model assigns a weighted score to each fuel option, incorporating both subjective evaluations (from fuzzy logic) and quantitative analyses (from the AHP model). This enables a thorough comparison among the fuels, providing insights into their relative effectiveness based on the priorities defined by the decision-maker. The outcomes of each scenario are examined to find the most appropriate fuel choice for specific conditions. These results are shared to assist decision-makers in understanding the trade-offs between different fuels, especially concerning cost efficiency, environmental effects, and safety [10]. Additionally, the model can be modified to investigate the impacts of changing parameters, like adjusting the weights of each criterion or trying out various fuel combinations. Ultimately, this phase seeks to deliver a clear, data-informed recommendation on the best fuel selection, customized to the specific requirements and limitations of the industry or company involved. The suggested decision acts as a framework for practical execution, ensuring that the chosen fuel aligns with both economic and environmental objectives [29].

2.3. Model Verifying and Validating

The final stage of this research involves verification and validation of the model. These steps are essential to ensure that the model is continually improved [30]. Verification checks the accuracy of the model based on the theoretical concepts used, while validation compares the model's data values with real-world values. The process is iterative, meaning it will be repeated until the model reaches a high level of accuracy. For model validation, Focus Group Discussions (FGD) are conducted, where a set of structured questions is asked to relevant stakeholders, including experts and practitioners. The goal is to gather feedback on the model's results and its alignment with real-world operations. The feedback from the FGD is analyzed and used to refine the model, ensuring its validity and practical applicability [31]. These verification and validation steps are repeated to improve the model’s accuracy and ensure it provides the best fuel selection solution for boiler systems [32].

3. Results and Discussion

In this section, the results obtained from using the DSM, based on the AHP and Fuzzy Logic methods for choosing fuels in boiler systems, are described. The evaluation focused on three different fuel sources—natural gas, diesel, and coal—while considering four main criteria: cost, calorific value, safety, and emissions. These criteria were carefully chosen through detailed interviews with industry professionals, highlighting their importance to operational effectiveness and environmental impact. Cost was prioritized because of its direct link to economic choices in various industries, especially in manufacturing, where cost reductions enable more competitive product pricing. Calorific value was chosen for its crucial impact on combustion efficiency, while safety and emissions were included to reduce risks and support environmental goals. Although fuel availability is a crucial factor in the fuel selection process, it was left out of this study due to a lack of reliable data. The availability of fuel resources, particularly concerning local supply chains and logistics, can greatly influence decisions about fuel selection. However, this data was found to be inaccessible or unmeasurable during this study. Additionally, despite the growing importance of renewable energy sources in industrial operations, they were not included in this research. This omission is mainly due to the study's focus on assessing traditional fossil fuels (natural gas, diesel, and coal) for existing boiler systems in sectors where renewable options have not yet been widely adopted or integrated. Future studies may explore the inclusion of renewable energy sources as part of a broader fuel selection strategy, especially as industries move towards sustainable energy practices.

3.1. Data Collecting

Based on the literature and interviews with industry experts, four main criteria were identified as the factors that most influence the selection of boiler fuel. These criteria are shown in table 1.

Table 1. Main Criteria

Criteria	Description
Cost	Measures the cost of using fuel, expressed in USD/mmBtu.
Heating Value	Measures the amount of energy produced by a fuel, expressed in Btu/lb.
Safety	Measures the level of safety associated with the use of a fuel, such as fire risk and health impacts.
Emissions	Measures the amount of carbon dioxide (CO2) emissions produced by burning a fuel, expressed in million metric tons.

Several criteria for boiler fuel will be included in the DSMs. The parameters proposed in this study are shown in table 2.

Table 2. Parameter Fuel

Parameter Fuel	Cost (USD/mmBtu)	Heating Value (Btu/lb)	Safety	Emission (Million metric tons)
Natural Gas	7.110	21,830	Strict	52.910
Industrial Diesel Oil (IDO)	20.230	18,900	Strict Enough	74.140
Coal	2.210	14,000	Moderate	95.990

3.2. Fuzzy Logic

An influence diagram illustrates the relationships between the parameters or variables used and the functions involved in decision-making, as shown in figure 2. The decisions made or taken should also have an impact on the areas that will be optimized (as the objectives of the decision). This diagram visually represents how different factors—such as cost, calorific value, safety, and emissions—affect the final decision, providing a clearer understanding of how each element influences the outcome. By mapping out these relationships, the influence diagram helps to structure the decision process and highlights the critical aspects that need to be considered to achieve the desired optimization in fuel selection for boiler systems as shown in figure 2.

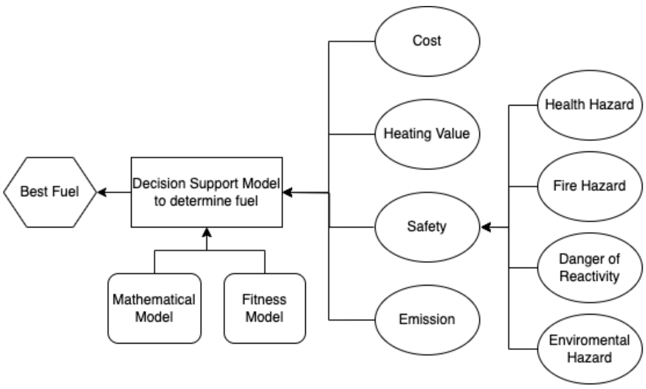

Figure 2. Influence Diagram

In this study, we define five different safety categories: "Not Strict", "Not Strict Enough", "Medium", "Fairly Strict", and "Strict". Each category will have a membership function that describes the degree to which an input value (safety) belongs to that category. The input range for safety is defined between 0 and 5, where 0 represents the lowest level of safety (Not Strict) and 5 represents the highest level of safety (Strict). The fuzzy membership functions for each category will be designed to reflect the degree of safety based on expert judgments and industry standards. These functions allow for a more nuanced assessment of safety in the fuel selection process, accommodating the inherent subjectivity and uncertainty in evaluating safety conditions. The use of fuzzy logic in this context provides a more flexible and realistic approach to decision-making, as it enables the handling of imprecise or vague data as shown in figure 3.

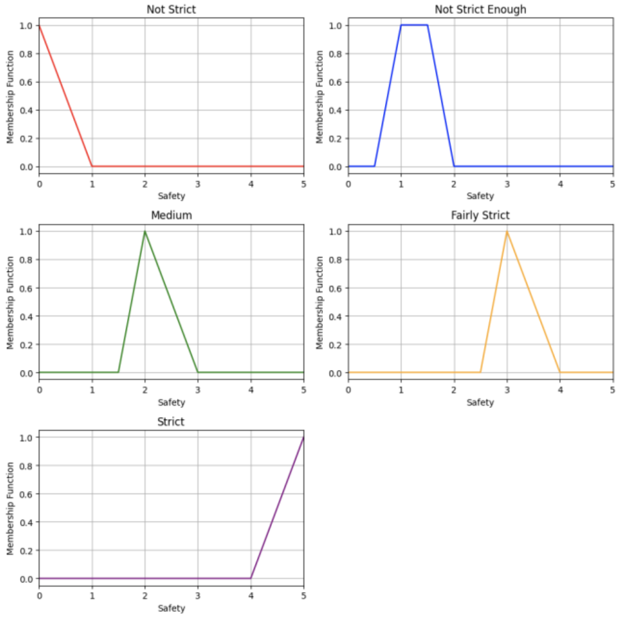

Figure 3. Membership Function Parameter Safety

Each parameter has five membership categories, meaning there are five possible categories for each parameter. Therefore, the total number of rule combinations for four input parameters with five categories each is 5 x 5 x 5 x 5 = 625 possible rule combinations. To formulate all the fuzzy rules, we will use a systematic approach based on the membership categories of each parameter. This study will develop a fuzzy logic system that will assess the safety of a fuel based on four parameters: Health Hazard, Fire Hazard, Danger of Reactivity, and Environmental Hazard. The output of this system will be the safety level, which is categorized into: "Not Strict," "Not Sufficiently Strict," "Medium," "Fairly Strict," and "Strict." The values of the sub-parameters, obtained through expert discussions, will serve as inputs for the fuzzification process. By using fuzzy logic, the model can effectively handle the uncertainties and subjectivity in evaluating the safety of fuels, providing a more flexible and realistic decision-making tool for fuel selection, as shown in table 3.

Table 3. Sub-Parameter Safety

Sub-Parameter Safety	Health Hazard	Fire Hazard	Danger of Reactivity	Environmental Hazard
Natural Gas	2	4	5	3
Industrial Diesel Oil (IDO)	3	2	2	2
Coal	1	3	0	4

For the fuzzy inference process, we use the Min (minimum) method to combine membership results based on the relevant rules. For example, if Health Hazard is "Medium," Fire Hazard is "Fairly Strict," Danger of Reactivity is "Strict," and Environmental Hazard is "Fairly Strict," the resulting safety classification could be either "Fairly Strict" or "Strict." The defuzzification process is then used to obtain a crisp value from the fuzzy output. In this case, the Centroid method is applied, which calculates the center of gravity of the area under the membership function curve. Based on this fuzzy calculation, the crisp output value for the Safety of Natural Gas is 4, which falls into the "Strict" safety category. This value is then used to make a clear decision about the safety level of Natural Gas in the context of fuel selection, as shown in table 4.

Table 4. Sub-Parameter Safety Natural Gas

Sub-Parameter	Input Value	Category
Health Hazard	2	Medium
Fire Hazard	4	Fairly Strict
Danger of Reactivity	5	Strict
Environmental Hazard	3	Fairly Strict

If Health Hazard = "Fairly Strict," Fire Hazard = "Medium," Danger of Reactivity = " Medium," and Environmental Hazard = " Medium," then the Safety classification could be either "Fairly Strict" or " Medium." Based on this fuzzy calculation, the crisp output value for the Safety of Industrial Diesel Oil (IDO) is 3, which falls into the "Fairly Strict" or " Medium " category. This value is used to assess the safety level of Industrial Diesel Oil in the fuel selection process, as shown in table 5.

Table 5. Sub-Parameter Safety Industrial Diesel Oil

Sub-Parameter	Input Value	Category
Health Hazard	3	Fairly Strict
Fire Hazard	2	Medium
Danger of Reactivity	2	Medium
Environmental Hazard	2	Medium

If Health Hazard = "Not Strict Enough," Fire Hazard = "Medium," Danger of Reactivity = "Not Strict," and Environmental Hazard = "Fairly Strict," then the Safety classification could be either "Not Strict Enough" or "Fairly Strict." Based on this fuzzy calculation, the crisp output value for Safety in Coal is 2, which falls into the " Medium" category. This value is used to assess the safety level of coal in the fuel selection process, as shown in table 6.

Table 6. Sub-Parameter Safety Coal

Sub-Parameter	Input Value	Category
Health Hazard	1	Not Strict Enough
Fire Hazard	2	Medium
Danger of Reactivity	0	Not Strict
Environmental Hazard	4	Fairly Strict

After completing all the stages of the fuzzy process, crisp values for each fuel alternative were obtained as follows: Natural Gas = 4, Industrial Diesel Oil = 3, and Coal = 2. These crisp values represent the final evaluation of each fuel alternative after applying the fuzzy logic process, where each alternative has been assessed based on the selected criteria (cost, calorific value, safety, and emissions) and their respective fuzzy membership functions. These crisp values provide a clearer and more actionable result, which can be used in further analysis or decision-making regarding the optimal fuel selection for boiler systems.

3.3. AHP Criteria Weighting

Each criterion is compared in pairs to assess its relative importance to each other. This decision-making is done through a pairwise comparison matrix, where each element of the matrix represents the degree of preference of one criterion over another. The following is a matrix of the results of the pairwise comparison, as shown in table 7.

Table 7. Pairwise Comparison Matrix

Criteria	Cost	Heating Value	Safety	Emission
Cost	1	3	4	4
Heating Value	1/3	1	3	4
Safety	1/4	1/3	1	3
Emissions	1/4	1/4	1/3	1

The criteria weighting in this research was carried out by interviewing experts and professionals with experience in the manufacturing sector, especially those working in boiler management and fuel selection. This weighting is determined by the practical importance of each criterion to industrial activities, along with the priorities seen in the field, ensuring that the choices made align with the actual practices of the manufacturing industry. Cost was given the highest importance since operational costs are a crucial element in assessing company performance and form a key part of the Key Performance Indicators (KPIs) utilized in various industries. Efficiency in operational costs is vital for staying competitive, especially in the manufacturing sector, which typically functions on narrow profit margins. Therefore, cost is prioritized in fuel selection. Heating Value was also given considerable importance, as fuels with higher calorific value perform better in combustion and can fulfill energy requirements using less fuel. In practical terms, achieving optimal combustion efficiency is key to reducing fuel usage and enhancing the overall effectiveness of the boiler system. Safety and Emissions received lower importance than cost and heating value, though both are still significant in fuel selection. Safety and emissions are deemed satisfactory as long as they comply with the standards set by the company and government regulations. In numerous manufacturing sectors, as long as safety and emissions standards adhere to the relevant regulations, they are not viewed as the primary factors in fuel selection. Thus, the weighting represents the priorities in the manufacturing sector, as established through discussions with industry professionals. This offers a strong and credible foundation for the methodology applied in the study, improving transparency in the decision-making process.

In this matrix, for each column in the matrix, calculate the total. Divide each element in the column by the total of that column to normalize the values in the matrix. Calculate the total of each column:

$$\text{Cost Column} \quad : 1+1/3+1/4+1/4 \quad = 1.833 \tag{1}$$

$$\text{Heating Value Column} \quad : 3+1+1/3+1/4 \quad = 4.583 \tag{2}$$

$$\text{Safety Column} \quad : 4+3+1+1/3 \quad = 8.333 \tag{3}$$

$$\text{Emissions Column} \quad : 4+4+3+1 \quad = 12.000 \tag{4}$$

Then, divide each element in the column by the total of that column to get the normalized value. The results can be seen in the following table 8.

Table 8. Normalized Value

Criteria	Cost	Heating Value	Safety	Emission
Cost	0,545	0,655	0,480	0,333
Heating Value	0,182	0,218	0,360	0,333
Safety	0,136	0,073	0,120	0,250
Emissions	0,136	0,055	0,040	0,083

From the pairwise comparison matrix, the eigenvector calculation is then carried out to determine the priority weight of each criterion. The result is a weight that shows how much influence each criterion has on the final decision, as shown in table 9.

Table 9. Priority Weight

Criteria	Average
Cost	0,503
Heating Value	0,273
Safety	0,145
Emissions	0,079

One of the advantages of AHP is its ability to check the consistency of paired comparison assessments. Consistency Index (CI) and Consistency Ratio (CR) are calculated to ensure that the assessments made do not contain high inconsistencies. Therefore, the calculation of the Index and CR is carried out with the following stages:

$$\text{Cost} \quad : 1\times0.503+3\times0.273+4\times0.145+4\times0.079 \quad = 2.217 \tag{5}$$

$$\text{Heating Value} \quad : 1/3\times0.503+1\times0.273+3\times0.145+4\times0.079 \quad = 1.190 \tag{6}$$

$$\text{Safety} \quad : 1/4\times0.503+1/3\times0.273+1\times0.145+3\times0.079 \quad = 0.597 \tag{7}$$

$$\text{Emissions} \quad : 1/4\times0.503+1/4\times0.273+1/3\times0.145+1\times0.079 \quad = 0.321 \tag{8}$$

Then, divide each of the above results by their respective priority weights:

$$\text{Cost} \quad : 2.217 \,/\, 0.503 \approx 4.40 \tag{9}$$

$$\text{Heating Value} \quad : 1.190 \,/\, 0.273 \approx 4.35 \tag{10}$$

$$\text{Safety} \quad : 0.597 \,/\, 0.145 \approx 4.12 \tag{11}$$

$$\text{Emission} \quad : 0.321 \,/\, 0.079 \approx 4.08 \tag{12}$$

Next is to calculate the maximum lambda by calculating the average of the results above:

$$\lambda\text{max} = \frac{4.40 + 4.35 + 4.12 + 4.08}{4} \approx \frac{16.96}{4} \approx 4.242 \tag{13}$$

Then calculate the CI using the formula:

$$\text{CI} = \frac{\lambda\,\text{max} - n}{n-1} \tag{14}$$

$$\text{CI} = \frac{4.242 - 4}{4 - 1} \approx \frac{0.242}{3} \approx 0.0807 \tag{15}$$

Finally, calculate the CR using the Random Index (RI) for the 4 criteria, which is 0.9. So:

$$\text{CR} = \frac{\text{CI}}{RI} \approx \frac{0.0807}{0.9} \approx 0.0897 \tag{16}$$

Generally, CR should be less than 0.1 to be considered consistent. CR: 0.0897. This shows that the assessment is consistent, so the calculated priority weights are reliable.

3.4. Evaluation of Alternative Fuels

After the priority weights of the criteria are obtained, the next step is to evaluate the fuel alternatives using Fuzzy Logic. Fuzzy inputs are taken from the AHP weight results, and three fuel alternatives (natural gas, diesel, coal) are evaluated based on the existing criteria. Before using the data for evaluation, each criterion is normalized to allow for fair comparison. The following are the results of data normalization, as shown in table 10:

Table 10. Data Normalization

Fuel	Cost	Heating Value	Safety	Emission
Natural Gas	0.311	1.000	1.000	1.000
Industrial Diesel Oil (IDO)	0.109	0.866	0.750	0.714
Coal	1.000	0.641	0.500	0.551

After normalization, fuzzy evaluation is performed to calculate the weighted value of each fuel alternative. Based on the fuzzy rules and priority weights of AHP, the following are the final assessment results, as shown in table 11:

Table 11. Final Assessment

Fuel	Weighted Value
Natural Gas	0.653
Industrial Diesel Oil (IDO)	0.456
Coal	0.794

From the above results, coal has the highest weighted value (0.794), followed by natural gas (0.653), and diesel (0.456). Coal excels mainly because it has a much lower cost compared to other fuels. However, natural gas scores the highest in the safety and emission criteria.

3.5. Simulation and Prototype Testing

At At this point, the prototype of the DSM is being tested with simulations to verify its effectiveness in real-life situations. The goal of this simulation is to assess how well the model can choose the optimal fuel for the boiler engine based on specific criteria and weights. The DSM's prototype is created using a mix of the AHP and Fuzzy Logic techniques. AHP helps in assigning weights to the criteria, while Fuzzy Logic is used to manage uncertainty in evaluating those criteria. The prototype is developed on Google Colab, utilizing the Python programming language. The pseudocode resulting from this prototype's development is shown in figure 4:

```
START
    1. Install and import the library
    2. Define input variables
    3. Define output variables
    4. Define membership functions for input and output.
    5. Define fuzzy rules
    6. Create a fuzzy control system with defined rules.
    7. Initialize the fuzzy control simulation.
    8. Define fuel data for each fuel
END
```

Figure 4. Pseudocode Script

From these results, coal is the most optimal fuel choice overall, with a value of 0.780 in the simulation. Natural Gas is in second place with a value of 0.624, while IDO has a value of 0.435. Coal excels mainly because of its very low cost, although it has disadvantages in terms of calories and safety. However, Coal also has advantages in terms of emissions, which makes it more environmentally friendly.

3.6. Model Verification and Validation

In this section, model validation is carried out by comparing the results of data processing obtained through two different approaches, namely simulation and prototyping using Google Colab and manual data processing using Microsoft Excel. This validation process is important to ensure that the developed model has an adequate level of accuracy and consistency in providing accurate and reliable results. The results of the comparison of the two approaches can be seen in the following table 12.

Table 12. Verification Model Comparison

Fuel	Comparison	
	Manual	Simulation
Natural Gas	0.653	0.653
Industrial Diesel Oil (IDO)	0.456	0.456
Coal	0.794	0.794

In the table above, it can be seen that the consistency between manual calculations and simulations shows that both methods provide similar results in the context of optimal fuel selection. It can be seen from the similarity of the preference order confirming that the developed model has successfully considered significant factors consistently, starting from Coal fuel, then Natural Gas, and finally IDO.

In this section, the model validation is carried out by comparing the processed data results obtained through the model with the actual data encountered in the field. The field data consists of monthly fuel consumption data for the boiler system from 2013 to 2023. After obtaining the actual data, the same data processing method, namely AHP Fuzzy, was applied for analysis. This validation process is essential to ensure that the developed model has an adequate level of accuracy and consistency in providing accurate and reliable results. The comparison between the actual data and the prediction results showed that out of 132 test data points, the model successfully predicted 116 data points correctly and mis predicted 16. Therefore, the model's accuracy rate is 87.88%, indicating that the developed model is valid and reliable, as shown in table 13.

Table 13. Validation Model with Historical Data

Fuel/ Ranking	Prediction			Actual		
	1	2	3	1	2	3
Natural Gas	0	132	0	16	116	0
Industrial Diesel Oil (IDO)	0	0	132	0	0	132
Coal	132	0	0	116	16	0

To measure the accuracy of the model's predictions compared to the actual data, two indicators were used: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The MAE value is 0.0526, showing the average difference between the predicted values and actual data. The RMSE value is 0.0640, which reflects the average squared difference between the predicted and actual values. Both metrics suggest that the model's predictions are close to the actual data, confirming that the model is reliable and accurate for decision-making.

4. Conclusion

This study aims to create a DSM based on the AHP and Fuzzy Logic methods to determine the best fuel for a boiler engine, considering four main criteria: cost, calorific value, safety, and emissions. The findings indicate that while coal remains the most cost-effective choice, natural gas emerges as a better option when safety and environmental sustainability are prioritized, due to its ability to produce lower carbon emissions. This makes natural gas more aligned with the growing need for fuels that adhere to strict environmental sustainability standards, such as reduced greenhouse gas emissions and more efficient combustion. The model's ability to combine both economic and environmental factors highlight its practical implications for industries seeking to balance cost-effectiveness with sustainability goals in fuel selection. However, the model's reliance on expert judgment and subjective assessments, especially during the fuzzy evaluation stage, may limit the accuracy of the results. Future research could improve the model by including additional factors, such as renewable energy sources, while also tackling the issues of data availability and uncertainty in real-world applications.

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5. Declarations

5.1. Author Contributions

Conceptualization: J.W., D.N.U.; Methodology: J.W.; Software: J.W.; Validation: J.W. and D.N.U.; Formal Analysis: J.W. and D.N.U.; Investigation: J.W.; Resources: J.W.; Data Curation: J.W.; Writing Original Draft Preparation: J.W. and D.N.U.; Writing Review and Editing: J.W. and D.N.U.; Visualization: J.W. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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