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Application of the Entropy Method and Multi-Attribute Utility Theory (MAUT) to a Decision Support System for Determining Priorities in Air Pollution Mitigation Based on Ambient Air Quality Monitoring Data at PT Indocement Tunggal Prakarsa Tbk. Bogor

Farhan Aditya Hidayatulloh[1*], Ahmad Refi Zaini[2], Kemas Muhammad Rafli Azhary[3], Bilal Abdul Wahid[4]
[1-4] Universitas Bina Sarana Informatika, Indonesia
email: *farhanadityahidayatulloh@gmail.com*[1]

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Abstract

This study aims to apply the Entropy and Multi-Attribute Utility Theory (MAUT) methods within a web-based Decision Support System (DSS) to determine air pollution mitigation priorities based on ambient air quality monitoring data at PT Indocement Tunggal Prakarsa Tbk., Bogor. The research addresses the problem that available monitoring data have not been specifically processed into objective and measurable mitigation-priority information. Secondary data were organized into 12 alternatives representing combinations of two monitoring stations and observation periods from January to June, using seven criteria, namely ISPU PM2.5, PM10, NO_2, SO_2, HC, CO, and O_3. The Entropy method was employed to generate objective criterion weights based on data variation, while MAUT was used to calculate utility values and rank the alternatives. The weighting results identified ISPU PM2.5 as the most dominant criterion, with a weight of 0.231710871. The MAUT results ranked Site Kecamatan Cileungsi–March first with a utility value of 0.841307511, followed by Site Utama Indocement–February with 0.750091317 and Site Utama Indocement–June with 0.696256962. Sensitivity analysis using ±10% and ±20% changes in the dominant criterion weight showed that the ranking order remained unchanged, with a Spearman rank correlation of 1.000. The developed web-based system successfully presents the calculation process, ranking results, and supporting information in a structured manner, demonstrating that the Entropy–MAUT combination provides an objective and stable approach for supporting air pollution mitigation-priority decisions.

Keywords: *Ambient Air Quality, Decision Support System, Entropy, MAUT, Mitigation Priority.*

INTRODUCTION

Air pollution has become a persistent global environmental challenge because its consequences extend beyond ecological degradation to public health, occupational comfort, and the continuity of industrial activities. The expansion of transportation, manufacturing, and energy-related activities has increased the spatial and temporal complexity of pollutant concentrations, making air quality management increasingly dependent on systematic environmental observation rather than isolated measurements (Iqbal et al., 2024). Pollutant concentrations are also shaped by meteorological and socioeconomic conditions, including temperature, humidity, wind speed, and patterns of human activity, which can produce substantial variations across locations and observation periods (Guo et al., 2024). These dynamics indicate that ambient air quality cannot be adequately understood through a single pollutant indicator or a static assessment because environmental conditions emerge from interactions among multiple factors. Recent advances in sensing, imaging, and computational technologies have strengthened the capacity to collect, process, and interpret air quality information continuously, creating opportunities to transform monitoring infrastructures into more intelligent environmental management systems (Elbestar et al., 2024). The central challenge has consequently shifted from merely obtaining air quality measurements toward extracting decision-relevant information from increasingly large and heterogeneous monitoring datasets.

PT Indocement Tunggal Prakarsa Tbk. in Citeureup, Bogor Regency, represents an industrial setting in which sustained attention to ambient air quality is important because production, material handling, transportation, and supporting operational activities may interact with surrounding environmental conditions. The company is supported by an Ambient Air Quality Monitoring System (AQMS) integrated with a logger and internal monitoring dashboard, enabling air quality parameters to be recorded periodically and presented through historical as well as real-time information. Comparable IoT-based monitoring architectures demonstrate that the integration of sensors, communication networks, data processing, and dashboards can improve the availability and accessibility of environmental information for operational monitoring (Lestari & Pangaribuan, 2025). Real-time monitoring systems can also incorporate automatic notifications, allowing deviations from predefined thresholds to be communicated more rapidly to relevant users (Azizah et al., 2025). Such technological infrastructure provides an important foundation for data-driven environmental management, but data availability alone does not necessarily determine which monitoring location, period, or environmental condition should receive immediate mitigation attention. Research on data-driven air quality analytics similarly emphasizes that monitoring data become more valuable when they are transformed into analytical information that can support decision-making rather than remaining solely as descriptive records (Sembiring et al., 2024). The managerial problem therefore concerns not only how to monitor ambient air quality but also how to convert multidimensional monitoring observations into an objective and operationally meaningful priority structure.

Previous research has demonstrated substantial progress in developing digital systems for air quality monitoring and decision support, although the dominant emphasis remains divided between monitoring infrastructure, prediction, visualization, and policy-oriented modelling. A web-based decision support tool, for example, has demonstrated how real-time air quality assessment can be integrated with analytical functions to support urban environmental management (Cau et al., 2025). At a larger policy scale, DSS v1.0 developed for Delhi integrates air quality forecasting, source apportionment, and emission-reduction scenario simulations, illustrating the potential of decision support technologies to move beyond observation toward evaluation of alternative mitigation strategies (Govardhan et al., 2024a). Cloud-based decision support research has similarly established the value of integrating air quality information into computational environments capable of supporting environmental management decisions (Evagelopoulos et al., 2022). These studies collectively indicate that contemporary air quality DSS development is moving toward integrated and data-driven architectures rather than standalone monitoring applications. However, the analytical logic used to determine mitigation priorities remains less developed than the technologies used to collect and visualize air quality information. Real-time IoT and web systems developed in other environments have primarily concentrated on data acquisition, dashboard presentation, and early-warning notification, leaving the subsequent problem of ranking mitigation priorities comparatively underexplored (Rahmadani et al., 2025).

The unresolved issue becomes more apparent when ambient air quality is considered as a multi-criteria decision problem in which several parameters, monitoring locations, and observation periods must be evaluated simultaneously. A high value of one pollutant indicator does not necessarily imply that an alternative should receive the highest mitigation priority when other indicators exhibit different magnitudes, frequencies, or relative conditions. Research on indoor air quality has shown that multi-attribute decision-making can be used to construct weighting schemes for prioritizing pollutants by incorporating technical, economic, and health-related considerations, demonstrating the relevance of objective weighting in complex air quality assessments (Piasecki & Kostyrko, 2020). In broader decision-making applications, the Entropy method has been employed to derive objective criterion weights from the informational variation contained in decision data, reducing dependence on purely subjective judgments (Hadad, 2024). MAUT provides a complementary decision framework because alternatives can be transformed into utility values and evaluated according to their relative performance across multiple attributes (Khazaei et al., 2026). Empirical applications have also shown that integrating Entropy weighting with MAUT can produce structured rankings by combining objective criterion weighting with utility-based alternative evaluation (Puspa et al., 2023). Yet the existing evidence does not sufficiently explain how this methodological combination can be operationalized using actual ambient air quality monitoring data from an industrial facility to establish mitigation priorities. This gap is particularly important because industrial environmental management requires a decision mechanism that is simultaneously data-driven, transparent, reproducible, and sufficiently flexible to accommodate heterogeneous monitoring conditions.

The practical relevance of this gap is reinforced by studies showing that air quality improvement requires the evaluation of multiple intervention alternatives rather than reliance on a single threshold-based response. Research on air quality improvement strategies in an urban transit-oriented development area, for instance, demonstrates the need to evaluate alternative control measures according to the characteristics of the environmental context (Ginting et al., 2025). Multi-criteria decision-making has also been applied within the cement-industry context, indicating that structured decision models can support complex industrial choices in which several criteria must be considered concurrently (Sihombing & Putro, 2024). The effectiveness of objective weighting has further been demonstrated through the integration of Entropy with other ranking methods, suggesting that the method can reduce subjectivity when criteria exhibit different levels of informational variation (Surahman, 2024). More recent decision-support developments increasingly emphasize automated and intelligent governance architectures in which environmental data are connected directly to prioritization and action-oriented decision processes (Rubio et al., 2026). Nevertheless, these developments have not yet established a specific methodological framework that connects company-level AQMS observations, objective Entropy weighting, MAUT-based utility assessment, and mitigation-priority ranking within an industrial air quality management system. The absence of such integration creates both a conceptual gap concerning how monitoring information should be translated into multi-criteria environmental priorities and an empirical gap concerning its implementation in a real industrial setting. Addressing this gap is scientifically important because it extends air quality DSS research from monitoring and forecasting toward explicit prioritization, while its practical importance lies in supporting environmental managers in allocating mitigation attention according to measurable evidence rather than isolated indicators or subjective judgments.

This study is positioned within the intersection of intelligent decision support, ambient air quality analytics, and multi-attribute decision-making by treating AQMS observations as decision data rather than merely monitoring outputs. The research applies the Entropy method to determine objective weights for the selected air quality criteria according to the information variation contained in the observed data, while MAUT is employed to transform criterion performance into utility values and generate a ranking of mitigation priorities. The resulting framework is designed specifically for the operational context of PT Indocement Tunggal Prakarsa Tbk., Citeureup, Bogor Regency, where multiple monitoring observations must be interpreted systematically to identify conditions requiring greater mitigation attention. The study aims to develop and implement a Decision Support System that determines priorities for air pollution mitigation based on ambient air quality monitoring data by integrating objective Entropy weighting with MAUT-based utility evaluation. The theoretical contribution lies in extending the application of multi-criteria decision-making to industrial ambient air quality management by connecting information-based weighting with utility-based prioritization within a unified analytical framework. The methodological contribution lies in demonstrating how routinely collected AQMS data can be transformed into a reproducible ranking mechanism that reduces reliance on subjective prioritization and provides an explicit analytical pathway from monitoring data to mitigation decisions. The resulting approach is expected to strengthen the role of intelligent engineering and computing in environmental management by providing a structured, transparent, and data-driven basis for determining which air pollution conditions should receive priority mitigation attention.

RESEARCH METHODS

The study is categorized as an empirical system-development study because it uses actual secondary data from the ambient air quality monitoring system of PT Indocement Tunggal Prakarsa Tbk. Bogor and implements the decision model into a Decision Support System (DSS). The system architecture consists of four principal layers: a data acquisition layer that receives historical AQMS data from the internal logger and monitoring dashboard, a data processing layer for data understanding, data preparation, and decision-matrix construction, a decision layer for Entropy weighting and MAUT ranking, and an application layer for presenting mitigation-priority results to users. IoT- and dashboard-based approaches provide a relevant technological foundation because air quality monitoring systems can integrate sensing, data communication, storage, and visualization to produce structured environmental information (Rahmadani et al., 2025). The dataset consists of historical secondary ambient air quality data represented by ISPU values for PM2.5, PM10, SO_2, O_3, NO_2, HC, and CO, with each alternative defined as a combination of a monitoring station and observation period. During the data understanding stage, the data source, observation period, monitoring stations, variable structure, measurement units, completeness, and characteristics of each parameter are examined, while the data preparation stage involves data selection, data cleaning, transformation, attribute identification, and construction of the decision matrix. The integration of automated notifications and structured data presentation further supports the operational function of environmental monitoring systems by enabling faster responses to air quality conditions requiring attention (Azizah et al., 2025). Once the dataset is prepared, the Entropy method is applied to obtain objective criterion weights based on the information content and variation of each criterion, while MAUT is employed to normalize alternative performance, transform it into utility values, multiply the utility values by the corresponding criterion weights, and aggregate the weighted utilities into final scores and mitigation-priority rankings.

The implemented model is evaluated quantitatively by reproducing the complete calculation sequence, including the decision matrix, normalization, Entropy values, criterion weights, MAUT utility values, final scores, and alternative rankings, so that every system output can be traced to its input data and underlying computational formula. In the Entropy calculation, the relative variation or information content of each criterion is used to establish objective weights, whereas MAUT transforms the performance of each alternative into utility scores that enable multiple attributes to be evaluated within a common decision scale (Khazaei et al., 2026). Functional testing is conducted by entering the prepared testing dataset into the application and examining whether the system produces outputs consistent with the predefined computational procedures, including criterion weights, utility values, final scores, and mitigation rankings. Numerical validation is performed by comparing the system outputs with independent calculations conducted using Microsoft Excel for all major components of the model, allowing errors in formula implementation, data processing, or numerical rounding to be identified directly. The integration of Entropy weighting and MAUT is particularly appropriate because previous applications have demonstrated its capability to combine objective criterion weighting with multi-attribute utility-based alternative ranking (Puspa et al., 2023). Model performance is evaluated using output agreement, defined as the percentage of consistency between the criterion weights, utility scores, final values, and ranking sequences generated by the application and those obtained from the independent reference calculations, with a target agreement of 100% or only negligible numerical differences attributable to rounding. The system is considered technically valid when all computational stages can be reproduced from the same dataset and the application generates mitigation-priority decisions identical to the independently calculated reference results.

RESULTS AND DISCUSSION

System Implementation and Integration of the Entropy–MAUT Decision Model

The implementation stage was carried out by developing a web-based Decision Support System (DSS) integrated with the ambient air quality monitoring system. The developed system is capable of managing and displaying monitoring data, determining criterion weights using the Entropy method, and ranking alternatives using the MAUT method. The alternatives consist of monitoring stations or locations that are compared based on air quality parameters to determine objective air pollution mitigation priorities. The system implementation includes several main features, namely the monitoring dashboard, station overview, priority analysis, calculation process, and reporting. The dashboard is used to present general air quality monitoring conditions, while the station overview provides information and status for each monitoring station. The priority-analysis and calculation pages subsequently connect monitoring information with the decision-making process through Entropy weighting and MAUT ranking.

The system interface was designed as a web-based dashboard with a sidebar navigation structure that provides access to all application functions. The available menus consist of Dashboard, Master Data, Priority Analysis (DSS), Stations, Station Maps, Reports, ISPU Validation, Early Warning, Channels, and Alarm Sound. This navigation structure allows users to perform monitoring, data management, priority analysis, and reporting within an integrated application environment. The arrangement also changes the function of air quality data from information used primarily for monitoring into information that can support more effective decision-making. The Monitoring Center Dashboard serves as the main page for presenting a summary of the air quality monitoring system. The displayed information includes total assets, network health, active alerts, and downtime, while the Device Explorer section provides a list of stations or loggers monitored by the system.

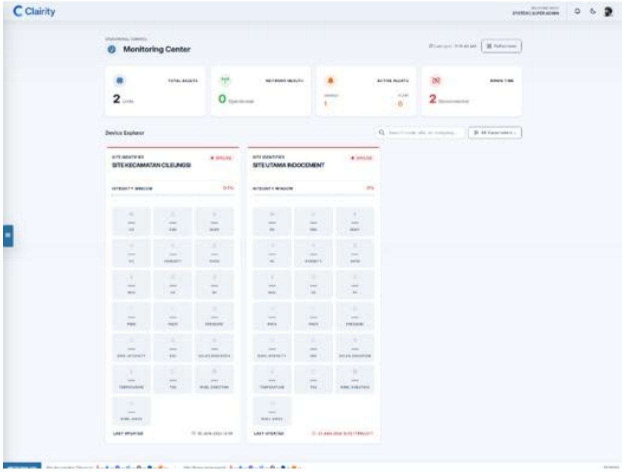

Figure 1. Monitoring Center Dashboard Page

Figure 1 presents the Monitoring Center Dashboard, which functions as the initial monitoring center before users proceed to the mitigation-priority analysis. The page provides an overview of the condition of monitoring devices and the availability of monitoring data within the system. The total assets indicator provides information regarding the monitored assets, while network health describes the operational condition of the connected monitoring infrastructure. Active alerts and downtime provide additional information that can help users identify conditions requiring attention. The Device Explorer further supports monitoring by presenting the stations or loggers registered in the system. Thus, the dashboard provides an initial operational overview that supports the subsequent use of monitoring data in the decision-support process.

The Priority Ranking and Status Analysis page is used to present the final output of the Decision Support System. The page displays stations or areas with the highest air pollution mitigation priority based on the utility scores generated by the MAUT method. The ranking table contains the rank, station identity, ISPU status, utility score, and recommendation, allowing users to directly compare the decision results among alternatives. Alternatives with higher utility scores are assigned higher priority, whereas alternatives with lower scores may receive a controlled status according to the resulting decision. The page therefore functions as a concise summary of the decision generated through the weighting and ranking processes. Because the displayed information represents the final output of the analysis, it can be used by users or management as a consideration for determining air pollution mitigation priorities.

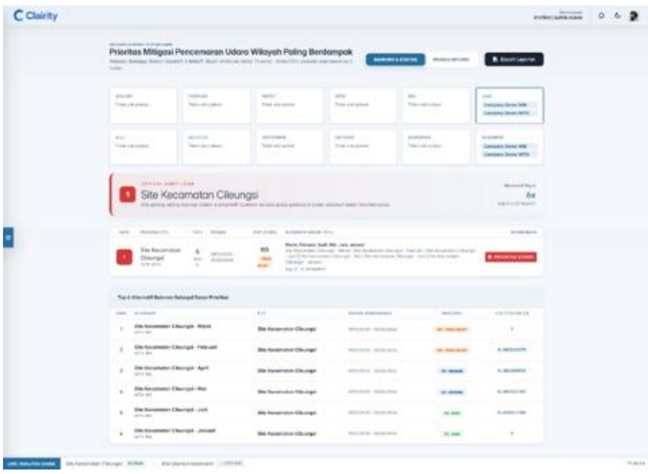

Figure 2. Priority Ranking and Status Analysis Page

The computational component of the system, referred to as code generation, implements the logical procedures and algorithms required for the Entropy and MAUT calculations. The implementation covers decision-matrix construction, Entropy normalization, proportion calculation, entropy calculation, dispersion calculation, objective weighting, MAUT normalization, utility calculation, and final ranking. The program code is organized in the form of traits so that the calculation procedures can be reused in a structured manner. The decision matrix contains monitoring stations or sites as alternatives and CO, HC, NO_2, O_3, PM10, PM2.5, and SO_2 as the air quality criteria. Data are obtained from the latest reading of each station through the latestReading relationship and matched with the parameter code corresponding to each criterion. If a parameter is found, its value is entered into the decision matrix, whereas a value of zero is assigned when the required parameter is unavailable.

After the decision matrix is formed, the system performs Entropy normalization to place the criterion values on a comparable scale. For benefit criteria, the implementation uses the value divided by the maximum value, whereas for cost criteria it uses the minimum value divided by the observed value. The normalized values are then accumulated for each criterion and used to calculate the corresponding proportions. The system subsequently calculates the natural logarithm of the proportion and the entropy value, followed by the dispersion value and the objective Entropy weight. The resulting weights are then used in MAUT normalization, utility calculation, and aggregation of the total MAUT score, after which alternatives are sorted from the highest to the lowest utility score. The implementation therefore establishes a direct correspondence between the mathematical calculation procedures and the computational functions used in the application, ensuring that the final ranking can be traced from the original monitoring data through each analytical stage.

Table 1. Correspondence Between Entropy and MAUT Formulas and System Code

Stage	Formula	Code Implementation	Description
Decision matrix	Xij	`$matriksKeputusan[$alt->id][$criteria->code] = $val;`	Forms alternative values against criteria
Maximum value	max(Xij)	`$max = max($values);`	Obtains the maximum value of each criterion
Minimum value	min(Xij)	`$min = min($values);`	Obtains the minimum value of each criterion
Entropy normalization – benefit	rij = Xij / max(Xij)	`$val / $max`	Normalization for benefit criteria
Entropy normalization – cost	rij = min(Xij) / Xij	`$min / $val`	Normalization for cost criteria
Total normalization	∑rij	`array_sum(array_column(...))`	Sums normalized values for each criterion
Proportion	Pij = rij / ∑rij	`$val / $total`	Calculates criterion proportions
Natural logarithm	ln(Pij)	`log($p)`	Calculates the natural logarithm
P × ln(P)	Pij × ln(Pij)	`$p * log($p)`	Calculates the entropy component
Entropy	Ej = (-1 / ln m) ∑[Pij × ln(Pij)]	`-$k * $sum`	Calculates entropy for each criterion
Dispersion	dj = 1 − Ej	`1 - $nilaiEntropy[...]`	Calculates information dispersion
Entropy weight	Wj = dj / ∑dj	`$nilaiDispersiEntropy[...] / $total`	Produces the objective weight
MAUT normalization	Uij = (Xij − min) / (max − min)	`($val - $min) / $range`	Calculates MAUT utility
Weighted utility	Wj × Uij	`$normal * $bobot`	Calculates criterion contribution
Total MAUT	Ui = ∑[Wj × Uij]	`$score += bobot * normalisasi`	Calculates the utility score

Ranking	Highest first	Ui	arsort($totalNilaiMAUT)	Orders alternative priorities

Table 1 confirms that the calculation stages described in the mathematical model have been implemented directly in the system code. The implementation covers the decision matrix, maximum and minimum values, Entropy normalization, proportions, logarithmic transformation, entropy, dispersion, objective weighting, MAUT normalization, weighted utility, total utility, and ranking. The arsort() function is used to arrange the alternatives according to their MAUT scores from the highest to the lowest value. The highest utility score consequently determines the highest mitigation priority displayed on the Priority Analysis page. This correspondence demonstrates that the system output is generated through a structured computational sequence rather than through manual assignment of priorities. The consistency between the Entropy weighting and MAUT aggregation stages also provides the computational basis for verifying the decision-support results against the underlying formulas.

Entropy Weighting and MAUT-Based Mitigation Priority Ranking

The decision analysis was conducted by applying the Entropy method to determine objective criterion weights before calculating mitigation priorities using MAUT. The seven criteria used in the analysis were ISPU PM2.5, ISPU PM10, ISPU NO_2, ISPU SO_2, ISPU HC, ISPU CO, and ISPU O_3. Each criterion represents an air quality parameter used to evaluate the condition of the monitoring alternatives. The Entropy method determines the relative importance of each criterion from the information distribution and variation contained in the decision matrix. This approach reduces dependence on subjective weighting because the resulting weights are derived from the characteristics of the observed data.

The use of Entropy weighting is appropriate for multi-criteria decision-making because criteria containing greater information variation can obtain greater objective weights (Hadad, 2024). The Entropy calculation begins with the normalized decision matrix, followed by the calculation of the proportion for each alternative and criterion. The proportion value is obtained by dividing the normalized value of an alternative by the total normalized value of the corresponding criterion. The system then calculates the natural logarithm of each proportion and multiplies it by the corresponding proportion to obtain the entropy component. When a proportion is equal to zero, the system assigns zero to the logarithmic component to prevent calculation errors. The entropy value for each criterion is subsequently calculated using the constant $1/\ln(m)$, where m represents the number of alternatives. This procedure enables the system to quantify the distribution of information contained in each of the seven criteria before determining their objective weights.

The next stage is the calculation of dispersion and objective Entropy weights. Dispersion is obtained from the difference between one and the entropy value, so a lower entropy value produces greater information dispersion. The resulting dispersion values are then divided by the total dispersion of all criteria to obtain the final criterion weights. Based on the sensitivity-analysis data provided in the study, ISPU PM2.5 (C1) obtained the largest initial weight of 0.231711, followed by ISPU HC (C5) at 0.194715 and ISPU CO (C6) at 0.152627. Meanwhile, ISPU SO_2 (C4), ISPU NO_2 (C3), ISPU O_3 (C7), and ISPU PM10 (C2) obtained weights of 0.111573, 0.109167, 0.101133, and 0.099074, respectively. The distribution shows that the seven criteria do not contribute equally to the decision model, with PM2.5 becoming the dominant criterion under the initial Entropy weighting.

Table 2. Initial Entropy Weights of Air Quality Criteria

Criterion	Parameter	Initial Weight
C1	ISPU PM2.5	0.231711
C2	ISPU PM10	0.099074
C3	ISPU NO_2	0.109167
C4	ISPU SO_2	0.111573
C5	ISPU HC	0.194715
C6	ISPU CO	0.152627
C7	ISPU O_3	0.101133

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Total	**1.000000**

Table 2 indicates that the initial weights sum to 1.000000, confirming that the objective weighting results are normalized. The highest contribution is provided by C1, namely ISPU PM2.5, with a weight of 0.231711, whereas C2, ISPU PM10, has the smallest weight at 0.099074. The difference between these values indicates that the information contribution of the criteria varies considerably within the observed dataset. The relatively high weights of PM2.5, HC, and CO mean that these three criteria collectively contribute 0.579053 of the total weighting. In contrast, the remaining four criteria collectively contribute 0.420947. This distribution becomes an important basis for the subsequent MAUT calculation because the criterion weights directly determine the contribution of each normalized criterion value to the final utility score.

After the Entropy weights are obtained, the system applies MAUT normalization to transform the performance of each alternative into a common utility scale. The normalization uses the minimum and maximum values of each criterion, with the benefit formulation expressed as $(X_{ij} - \min)/(\max - \min)$. In the context of the study, higher air quality parameter values indicate greater potential impact from air pollution and therefore produce higher utility values and potentially higher mitigation priorities. The normalized utility value for each criterion is multiplied by its corresponding Entropy weight to obtain the weighted utility contribution. These weighted contributions are then summed across all seven criteria to produce the total MAUT utility score for each alternative. This procedure allows alternatives with different combinations of pollutant conditions to be evaluated using a single aggregated decision value (Khazaei et al., 2026).

The final mitigation priority is determined by ordering the total MAUT scores from the highest to the lowest value. The alternative with the highest utility score is assigned the highest mitigation priority because it represents the strongest combined result across the evaluated air quality criteria. The ranking procedure is implemented using arsort($totalNilaiMAUT), after which the system assigns ranking numbers to the sorted alternatives. This process ensures that the ranking displayed on the Priority Analysis page directly corresponds to the calculated MAUT utility scores. The combination of objective Entropy weighting and MAUT aggregation provides a transparent analytical sequence from air quality observations to mitigation priorities. Previous research has also demonstrated the application of Entropy and MAUT as a combination for objective weighting and multi-criteria alternative ranking in decision-support systems (Puspa et al., 2023).

Usability Evaluation of the Decision Support System

The usability evaluation was conducted to determine whether the developed Decision Support System could be used effectively by its intended users. The evaluation consisted of two stages, namely a pre-test involving three experts and a post-test involving 20 respondents. The pre-test was conducted to identify weaknesses in the initial version of the system before it was evaluated by a larger group of users. The expert evaluation focused on the suitability of the interface, functionality, information presentation, and overall usability of the system. Feedback obtained from the experts was subsequently used as a basis for improving the system before the post-test was conducted. This two-stage evaluation provided an opportunity to identify and correct usability issues before measuring the final level of user acceptance. The approach also ensured that the usability assessment considered both expert judgment and direct user responses.

The pre-test involved three experts who assessed the initial implementation of the Decision Support System. The evaluation was intended to identify aspects of the application that required improvement before the system was distributed to the larger respondent group. The experts examined whether the available functions were understandable and whether the information presented by the system could support the intended monitoring and decision-making activities. Their feedback provided qualitative input regarding the usability and presentation of the application. Improvements were subsequently implemented based on the identified issues so that the revised system could provide a more appropriate user experience. This process is important because usability problems identified during an early evaluation can be addressed before the system is subjected to broader user testing. The revised system was then used as the basis for the post-test evaluation involving 20 respondents.

The post-test was conducted with 20 respondents using a questionnaire consisting of 10 statements. Each statement was evaluated using a five-level Likert scale, allowing respondents to express their level of agreement with the usability aspects being assessed. The use of a five-level scale provides a structured method for converting individual perceptions into numerical scores. Based on the results, the respondents produced a total score of 865 out of a maximum possible score of 1,000. The resulting percentage was therefore 86.5%, indicating that the developed system achieved a Very Feasible category. The score demonstrates that the majority of the evaluated usability aspects were positively perceived by the respondents. These results provide quantitative evidence that the revised Decision Support System was considered suitable for supporting the intended monitoring and mitigation-priority activities.

Table 3. Post-Test Usability Evaluation Results

Evaluation Component	Result
Number of respondents	20
Number of statements	10
Likert scale	5 levels
Maximum score	1,000
Obtained score	865
Percentage	86.5%
Category	Very Feasible

The results in Table 3 show that the obtained score reached 865 points, compared with the maximum possible score of 1,000 points. The difference between the maximum and obtained scores was therefore 135 points, indicating that the system did not receive a perfect usability score but achieved a high overall evaluation. The calculated percentage of 86.5% places the system in the Very Feasible category according to the evaluation criteria used in the study. This result indicates that the respondents generally considered the system understandable and appropriate for its intended function. The high percentage also suggests that the interface and functions implemented after the expert evaluation were sufficiently acceptable to the respondent group. From a decision-support perspective, good usability is important because users must be able to understand monitoring information and interpret the resulting mitigation priorities without unnecessary difficulty. Therefore, the post-test results support the feasibility of the developed system from the user perspective.

The usability results also demonstrate the importance of combining system functionality with an interface that can communicate analytical results clearly. The developed application does not only present monitoring information but also provides priority rankings generated through the Entropy and MAUT calculations. Users therefore need to understand both the information displayed by the interface and the meaning of the resulting utility scores and recommendations. The availability of dashboard, station, priority-analysis, and calculation features supports this requirement by providing different levels of information within the same application. The calculation process also increases transparency because users can examine how the Entropy and MAUT methods contribute to the final decision. This characteristic is relevant for data-driven air quality management because decision makers require information that is not only available but also interpretable and traceable (Sembiring et al., 2024). Consequently, the usability evaluation complements the technical implementation by demonstrating whether the analytical functions can be practically accessed and understood by users.

Overall, the usability evaluation indicates that the developed Decision Support System has achieved a high level of acceptance among the evaluated respondents. The combination of expert pre-testing and a 20-respondent post-test provided a sequential evaluation process from system improvement to quantitative usability assessment. The final score of 86.5% and the Very Feasible category indicate that the revised system was considered suitable for its intended use. The result also strengthens the practical value of integrating ambient air quality monitoring with Entropy-based weighting and MAUT-based priority ranking. However, the usability score should be interpreted specifically as an evaluation of system feasibility and user perception rather than as a direct measure of the accuracy of the air quality data or mitigation decisions. The technical reliability of the decision model therefore remains dependent on the quality of the monitoring data and the stability of the resulting rankings. Further evaluation through sensitivity analysis is consequently required to determine how robust the mitigation priorities are when the criterion weights or decision-model conditions are changed.

Sensitivity Analysis and Robustness of Mitigation Priority Ranking

Sensitivity analysis was conducted to evaluate the robustness of the mitigation-priority ranking generated by the Entropy–MAUT model. The analysis examined whether changes in criterion weights or criterion structure would cause changes in the ranking of the 12 evaluated alternatives. Seven criteria were initially used, with ISPU PM2.5 (C1) identified as the dominant criterion based on its initial Entropy weight of 0.231711. The sensitivity analysis was structured into scenarios S0 through S7, where S0 represented the original Entropy weights and S1–S4 represented changes of −20%, −10%, +10%, and +20% in the weight of C1. Scenario S5 tested sequential ±20% changes for all seven criteria, while S6 applied equal weighting and S7 restored three previously eliminated criteria to produce a 10-criterion structure. This design enabled the robustness of the ranking to be examined under both moderate weight changes and structural changes in the decision model.

Table 5. Sensitivity Analysis Scenario Design

Scenario Code	Description
S0	Initial Entropy weight
S1	W(C1) −20%
S2	W(C1) −10%
S3	W(C1) +10%
S4	W(C1) +20%
S5	±20% variation for all criteria
S6	Equal weights, 1/7 = 0.142857
S7	10-criterion structure

The results of scenarios S1–S4 demonstrate that changes in the dominant PM2.5 weight did not alter the ranking of the 12 alternatives. When the weight of C1 was reduced by 20%, its value changed from 0.231711 to 0.185369, whereas an increase of 20% raised it to 0.278053. The other criterion weights were adjusted proportionally so that the total weight remained 1.000000 in every scenario. Despite these changes, the Spearman correlation coefficient between each scenario and the initial ranking remained $\rho = 1.000$. The three highest-priority alternatives also remained consistent, namely Site Kecamatan Cileungsi–Maret, Site Utama Indocement–Februari, and Site Utama Indocement–Juni. The utility score of Site Utama Indocement–Juni, for example, changed from 0.696257 under S0 to 0.677936 under S1 and 0.714578 under S4, while its third-place ranking remained unchanged.

Table 6. Criterion Weight Composition under Scenarios S0–S4

Criterion	S0	S1 (−20%)	S2 (−10%)	S3 (+10%)	S4 (+20%)
C1 ISPU PM2.5	0.231711	0.185369	0.208540	0.254882	0.278053
C2 ISPU PM10	0.099074	0.105050	0.102062	0.096086	0.093098
C3 ISPU NO_2	0.109167	0.115752	0.112460	0.105875	0.102583
C4 ISPU SO_2	0.111573	0.118303	0.114938	0.108208	0.104843
C5 ISPU HC	0.194715	0.206459	0.200587	0.188842	0.182970
C6 ISPU CO	0.152627	0.161833	0.157230	0.148024	0.143421
C7 ISPU O_3	0.101133	0.107233	0.104183	0.098083	0.095033
Total	**1.000000**	**1.000000**	**1.000000**	**1.000000**	**1.000000**

The stability observed in S1–S4 was further examined through scenarios S5, S6, and S7 to determine whether the ranking remained robust under broader modifications. In S5, each of the seven criteria was individually varied by ±20%, resulting in 14 separate tests, while S6 replaced the Entropy weights with equal weights of 0.142857 for all criteria. Both S5 and S6 produced zero ranking changes and a Spearman coefficient of 1.000. In contrast, S7 modified the decision structure by adding the maximum ISPU, average ISPU, and number of exceedances of the quality standard, resulting in a total of 10 criteria. Under S7, three alternatives changed rank, while the Spearman coefficient decreased slightly to 0.979. The ranking changes were limited to the first three positions, whereas the remaining nine alternatives retained their original positions.

Table 7. Summary of Test Results for Scenarios S5–S7

Scenario	Alternatives with Changed Rank	ρ	First-Ranked Alternative
S5: W(C1) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C2) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C3) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C4) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C5) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C6) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S5: W(C7) ±20%	0	1.000	Site Kecamatan Cileungsi – Maret
S6: Equal weights	0	1.000	Site Kecamatan Cileungsi – Maret
S7: 10-criterion structure	3	0.979	Site Utama Indocement – June

The additional critical-threshold analysis was performed to determine the minimum weight change required to produce the first actual ranking change. The procedure gradually increased and decreased the weight of each criterion until a change in ranking was observed for the first time. This analysis provides a more detailed assessment than the fixed ±10% and ±20% scenarios because it identifies the point at which the ranking becomes sensitive to changes in criterion importance. A stable ranking under moderate changes indicates that the decision model is not easily affected by small variations in the Entropy weights. Conversely, a relatively small critical change would indicate that the corresponding criterion has a stronger influence on the ordering of alternatives. The critical-threshold results are therefore useful for interpreting the degree of confidence that can be placed in the mitigation-priority ranking.

Overall, the sensitivity analysis demonstrates that the mitigation-priority ranking generated by the seven-criterion Entropy–MAUT model is highly robust to changes in criterion weighting. Variations of up to ±20% in individual criterion weights did not change the ranking, and the equal-weight scenario also produced a Spearman correlation of 1.000. The ranking was affected only when the structure of the criteria was changed from seven to ten criteria, producing three ranking changes and a correlation coefficient of 0.979. This result indicates that the ranking is more sensitive to changes in the composition of the decision criteria than to moderate changes in the numerical weights assigned to the existing criteria. The consistent position of Site Kecamatan Cileungsi–Maret as the first-ranked alternative across the tested scenarios further supports the stability of the primary mitigation recommendation. Therefore, the sensitivity analysis provides empirical support that the proposed Entropy–MAUT model can produce relatively consistent mitigation priorities under reasonable variations in weighting conditions and decision-model configuration.

CONCLUSION

Based on the results of the analysis, design, implementation, system testing, and manual calculation verification using Microsoft Excel, this study successfully developed a web-based Decision Support System (DSS) for determining air pollution mitigation priorities based on ambient air quality monitoring data at PT Indocement Tunggal Prakarsa Tbk. The monitoring dataset consisted of 12 alternatives representing combinations of the Site Utama Indocement and Site Kecamatan Cileungsi locations during the January–June observation period and was evaluated using seven air quality criteria, namely ISPU PM2.5, PM10, NO_2, SO_2, HC, CO, and O_3. The Entropy method successfully generated objective criterion weights based on data variation, with ISPU PM2.5 obtaining the highest weight of 0.231710871 and becoming the most influential criterion in determining mitigation priorities. The resulting weights were subsequently incorporated into the Multi-Attribute Utility Theory (MAUT) method to calculate the utility values of each alternative and systematically establish their priority rankings. The calculation results showed that Site Kecamatan Cileungsi–March obtained the highest utility value of 0.841307511 and became the main mitigation priority, followed by Site Utama Indocement–February and Site Utama Indocement–June. In contrast, Site Kecamatan Cileungsi–January obtained the lowest utility value of 0 and occupied the final rank, demonstrating that the system was able to distinguish mitigation priorities among alternatives in a measurable and systematic manner. These findings confirm that the integration of Entropy and MAUT can transform multidimensional ambient air quality monitoring data into an objective and structured mitigation-priority ranking.

The sensitivity analysis further demonstrated that the Entropy–MAUT combination produced a highly stable and robust decision model under variations in criterion weights. Changes in the ISPU PM2.5 weight of ±10% and ±20%, changes of ±20% in individual criteria, and the application of equal criterion weights did not change the ranking order, as indicated by a Spearman rank correlation coefficient of 1.000. A ranking change occurred only when the weight variation exceeded 34.1%, while the first-ranked alternative remained unchanged when the weight variation was below 93%. These findings indicate that the mitigation-priority results are not easily affected by moderate changes in criterion weighting and therefore provide a consistent basis for decision-making. In addition to the analytical model, the developed DSS provides supporting features including a monitoring dashboard, master-data management, Entropy and MAUT calculation processes, reporting, ISPU validation, and early-warning functionality. These features improve the transparency of the monitoring and decision-making process by allowing users to access monitoring information and understand how mitigation priorities are generated. Overall, the study successfully implemented Entropy and MAUT within a web-based DSS that can support air pollution mitigation-priority determination in an objective, systematic, consistent, and comprehensible manner, thereby providing useful decision-support information for the evaluation and management of ambient air quality at PT Indocement Tunggal Prakarsa Tbk. Bogor.

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