Decision Support Model of Rice Seeds Selection using Hybrid Multi Criteria Decision Making

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Abstract

The initial stage in rice farming is the selection of rice seeds. To ensure a decent crop, seed selection must be taken into account. A decision support system may be a solution to this issue since the selection of the best rice seeds includes numerous elements connected to the considerations and preferences of each farmer group region. In this research, eight criteria were utilized to choose rice seeds: seed purity and uniformity, disease and pest resistance, agronomic traits, maturation and growth duration, environmental adaptability, farmer feedback and performance, yield potential, and grain quality. The weighting techniques utilized in this research are an arrangement of the Analytical Hierarchy Process and the Profile Matching Algorithm. When compared to expert judgements, the outcomes of this method's recommendations have a low error rate, with a MAPE value of 6.5%.

Keywords: Rice Seed, Decision Support System, Multi-criteria Decision Making

Introduction

Selecting the best rice seed according to the environment is essential for optimizing yield potential, managing risks, reducing reliance on external inputs, and promoting sustainable agriculture practices. By matching the seed characteristics to the specific environmental conditions, farmers can enhance crop performance, increase productivity, and ensure more resilient and sustainable rice production. According to Rathore et al. (2020), rice plants can be susceptible to various diseases and pests, which can significantly impact crop productivity. Different rice varieties exhibit varying levels of resistance or tolerance to specific diseases and pests. By selecting seeds that are known to have resistance to prevalent diseases or pests in a particular environment, farmers can reduce the risk of crop losses and minimize the need for excessive pesticide use.

Moreover, Wassmann et al. (2019) mentioned that rice varieties can differ in their inherent yield potential under different environmental conditions. Some varieties may perform better in high rainfall areas, while others may be more suitable for drought-prone regions. By selecting rice seeds that are specifically bred or adapted for the local environment, farmers can optimize the crop's yield potential and increase their chances of obtaining higher yields (Ying et al., 2019). Different environments have varying availability of resources such as water, nutrients, and sunlight. By selecting rice seeds that are suited to the specific environmental conditions, farmers can optimize the utilization of these resources (Javaid et al., 2023). For example, drought-tolerant varieties can be selected for regions with limited water availability, while nitrogen-efficient varieties can be chosen for areas with nutrient limitations. This helps maximize resource use efficiency and reduce wastage.

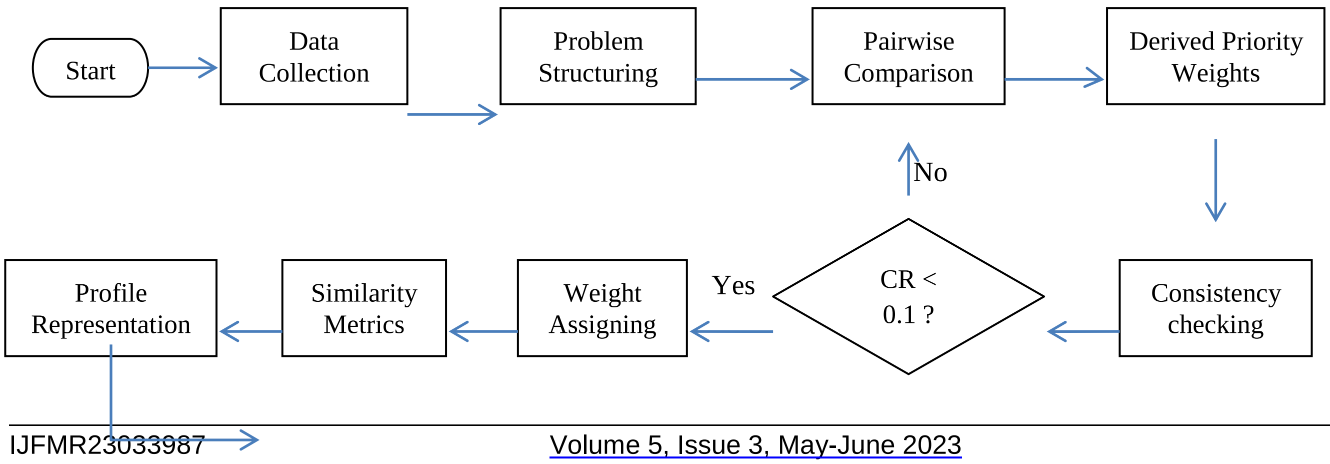
Selecting the best rice seeds involves considering multiple factors related to the specific requirements of farming operation, environmental conditions, market demands, and the desired characteristics of the rice crop (Maraveas et al., 2023). There are some steps that is commonly used in the selection process.

1. Identify the farming objectives, goals and priorities. Consider factors such as yield potential, disease resistance, grain quality, market demand, and any specific traits or characteristics that is preferred value in rice varieties.
2. Understand environmental conditions, crop duration and growth cycle, yield potential and performance, grain quality and market requirements, seed availability, and cost. Assessing multiple factors of farming area and identify any specific challenges or constraints that may impact rice cultivation in the region.
3. The data obtained in previous step then is consulted to local experts. Seek advice from local agricultural extension services, seed companies, or experienced farmers in the area. They can provide valuable insights into the performance of different rice varieties in the specific location. Additionally, refer to scientific research, agricultural publications, and seed catalogs for information on recommended varieties suitable for the region.
4. Use decision support system to help the decision-making process which involves multiple criteria. Many real-world decision problems involve multiple criteria that are often conflicting or interrelated. MCDM methods provide a structured approach to handle this complexity by considering and balancing multiple criteria simultaneously. They allow decision-makers to capture the multidimensional nature of the decision problem and make informed choices.

Research Method

This study combines 2 methods in Multi Criteria Decision Making (MCDM), namely Analytical Hierarchy Process (AHP) and Profile Matching Algorithm (PMA). AHP was employed due to its ability to provides a structured framework for decision-making, allowing decision-makers to break down complex problems into a hierarchy of criteria, sub-criteria, and alternatives (Bari et al., 2022). This hierarchical structure helps organize and analyze information systematically. To enhance the decision making process, we employed PMA. This method provide users with a clearer understanding of their options and the relative compatibility of different profiles (Rodriguez and Chavez, 2019). This helps users make more informed decisions based on objective and subjective criteria, leading to potentially better outcomes in areas such as personal recommendation, job recruitment, or sport-player matching.

Figure 1 shows the flowchart used in this study which combine AHP and PMA steps.



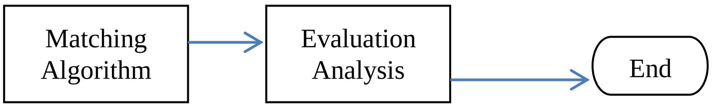


Figure 1. System Flowchart

Analytical Hierarchy Process (AHP)

AHP is known for its ability to handle complex decision problems, accommodate subjective judgments, and provide a systematic framework for decision-makers to evaluate alternatives (Canco et al., 2021). It enables decision-makers to incorporate both qualitative and quantitative factors, making it a versatile tool for a wide range of applications such as project selection, resource allocation, risk assessment, and supplier evaluation (Kumar and Kumar, 2019). AHP is widely used to solve complex problems and make decisions by systematically structuring and analyzing criteria and alternatives. AHP provides a framework for prioritizing and comparing multiple criteria or factors in a hierarchical manner. The AHP process involves the following key steps (Katarina et al., 2021):

1. Problem Structuring
   The first step is to define the decision problem and establish a hierarchical structure. The hierarchy consists of a goal, criteria, sub-criteria, and alternatives. The goal represents the overall objective, criteria represent the main factors influencing the decision, sub-criteria break down the criteria further, and alternatives are the potential options to be evaluated.
2. Pairwise Comparisons
   In this step, pairwise comparisons are made between the elements of each level in the hierarchy. Decision-makers compare the relative importance or preference of each element against every other element at the same level. These comparisons are expressed using a numerical scale, typically ranging from 1 to 9, with 1 indicating equal importance and 9 indicating extreme preference.
3. Deriving Priority Weights
   Based on the pairwise comparisons, priority weights are derived for each element of the hierarchy. These weights reflect the relative importance of the elements in relation to the goal. The weights are obtained by computing the normalized eigenvector of the comparison matrix, which is constructed from the pairwise comparison data.
4. Consistency Check
   AHP includes a consistency check to ensure the reliability of the pairwise comparisons. Consistency refers to the degree of coherence in the decision-maker's judgments. If the consistency ratio exceeds a predefined threshold, adjustments are made to the pairwise comparisons to enhance consistency.
5. Aggregation and Ranking
   The priority weights obtained from the pairwise comparisons are aggregated through a process called hierarchical synthesis. This process involves multiplying the weights along the branches of the hierarchy to obtain the overall priorities for each alternative. The alternatives are then ranked based on their overall priorities, providing a basis for decision-making.

Generally, there are three ways to evaluate the AHP method:

1. Consistency Ratio
   The consistency ratio is a measure of the consistency of the pairwise comparisons made by the decision-maker. It helps determine the reliability of the judgments provided. The consistency ratio is calculated by comparing the consistency index (CI) of the pairwise comparison matrix with a random index (RI) derived from the matrix's size. If the consistency ratio exceeds a predefined threshold (usually 0.1), it indicates that the judgments are inconsistent, and adjustments may be required.
2. Sensitivity Analysis
   Sensitivity analysis involves examining the impact of changes in the pairwise comparisons on the final priorities and rankings. By adjusting the pairwise comparison judgments and observing the resulting changes in the priorities, decision-makers can assess the stability and robustness of the AHP results. Sensitivity analysis helps identify critical factors or inconsistencies that significantly affect the decision outcomes.
3. Expert Validation
   Seek expert validation by involving domain experts or subject matter experts in the evaluation process. Experts can review the problem structuring, pairwise comparisons, and overall AHP methodology to provide feedback and assess the soundness of the approach. Their input can help identify potential biases, inconsistencies, or improvements in the AHP implementation.

In this study, the AHP is evaluated using consistency ratio which is obtained from comparison of consistency index (CI) and random index (RI) due to its less subjective and simplicity.

Profile Matching Algorithm

Profile matching algorithms are used to compare and match profiles or user preferences in various contexts, such as decision support tools, personalized recommendations, and social networking. These algorithms aim to find the most compatible or similar profiles based on specific criteria or attributes. The exact implementation of profile matching algorithms can vary depending on the context and the specific requirements of the application. Cucus et al. (2022) mentioned a general overview of how profile matching algorithms work as follows:

1. Profile Representation
   Each profile is typically represented as a set of attributes or features that describe the characteristics or preferences of the user. For example, in a seed plant recommendation app, attributes may include shape, weight, disease and pest resistant, price, and availability.
2. Distance between profile
   Profile matching algorithms measure the distance to quantify the similarity or compatibility between two profiles. The choice of metric depends on the nature of the attributes and the requirements of the application. Commonly used metrics include Euclidean distance, cosine similarity, and profile gap.
3. Weighting and Importance
   Not all attributes may have equal importance in determining the compatibility between profiles. Profile matching algorithms often allow for assigning weights or importance factors to different attributes. These weights reflect the relative significance of each attribute in the matching process.
4. Matching Algorithm

Once the profiles are represented and the similarity metrics are defined, a matching algorithm is applied to compare and rank the profiles. The algorithm calculates the similarity scores or distances between profiles and produces a ranked list of matches or recommendations.

5. Thresholds and Filtering
   Depending on the application, certain thresholds or filters may be applied to the matching results. For example, a prsonalized recommendation app may filter out profiles that fall below a certain compatibility threshold or exclude profiles that do not meet specific criteria.

Additionally, profile matching algorithms can be considered relatively simple compared to more complex algorithms used in areas such as machine learning or data mining. Typically, profile matching algorithms focus on comparing attributes or features of profiles. These attributes can be categorical (e.g., shape, pricing range) or numerical (e.g., weight, height). The comparison is often done using straightforward similarity metrics like Euclidean distance or profile gap. This attribute-based matching is conceptually simpler than analyzing complex patterns or relationships in large datasets. In this study, we use profile gap which is find the difference between the target value and the actual value of each alternative. This value is then transformed using the similarity metrics table (Prabowo, 2022) which is shown at Table 1.

Furthermore, Maulana et al. (2022) identified that profile matching algorithms typically rely on a predefined set of rules or criteria for comparing profiles. These rules are often based on explicit preferences or requirements specified by users. Compared to more advanced algorithms that learn patterns from data or make complex decisions, the rule-based nature of profile matching algorithms keeps them relatively simple.

Table 1. Gap Profile Metrics

Gap	Score	Description
0	5	No Gap (Competence as required)
1	4.5	Individual competence excess of 1 level
-1	4	Individual competence lacks 1 level
2	3.5	Individual competency excess of 2 levels
-2	3	Individual competencies lack 2 levels
3	2.5	Individual competence excess 3 levels
-3	2	Individual competence lacks 3 levels
4	1.5	Individual competence excess 4 levels
-4	1	Individual competence lacks 4 levels

Daheri et al. (2022) reported that the narrower focus allows for simplification as the algorithm can prioritize specific attributes or factors relevant to that context. This simplification enables efficient and targeted matching within a limited scope. Chai et al. (2022) mentioned that typically profile matching algorithm provide quick results to users. They aim to generate a ranked list of matches or recommendations in real-time or near real-time. The emphasis on speed and responsiveness often requires simpler algorithms that can process profiles and calculate similarity scores rapidly.

While profile matching algorithms are generally considered simple, it's important to note that simplicity is relative and depends on the specific requirements and complexity of the application. Profile matching algorithms can still involve various considerations and complexities, such as handling missing data, incorporating user feedback, or addressing scalability issues. The simplicity of these algorithms is often a trade-off between computational efficiency and the specific needs of the application.

Results And Discussion

After conducting interviews for the preliminary research, we conducted an inquiry to determine the issue affecting the Tani Jaya farmer group. Our conversation has led us to the conclusion that choosing the best rice seeds is done manually, one at a time, and that technology and scientific knowledge about rice plants are not fully developed. Following the problem's identification, interviews were also performed to collect information on the standards for rice seeds, alternate rice seeds, target value, expectations for the best rice seeds, and evaluation of alternative candidates. To gain information on the type of paddy, data is also gathered through direct observation of the area and from stores that sell rice seeds. Data collection takes about 3 months. Literature analysis is used to support theories by gathering evidence from literature sources including journals, archives, articles, and papers, and it is then compared to earlier studies to examine relevant issues. The criteria that are investigated in this study were obtained from literature (Pooter and Roos, 2021; Paul et al., 2021; Takahasi et al., 2019) and majority voting of experts in Tani Jaya Farmer Group. Each of those criteria is explained below.

1. Seed Purity and Uniformity (C1)
   Ensure that the selected rice seeds have high genetic purity and uniformity. Seeds with minimal genetic impurities and high uniformity provide more consistent and predictable crop performance.
2. Disease and Pest Resistance (C2)
   Choose rice seeds that possess resistance or tolerance to prevalent diseases and pests in the region. Resistance to diseases like blast, bacterial leaf blight, sheath blight, and pests such as stem borers and rice bugs can help minimize losses and reduce the need for excessive pesticide use.
3. Agronomic Traits (C3)
   Consider agronomic traits such as plant height, tillering capacity, lodging resistance, and straw strength. These traits can impact ease of management, harvesting efficiency, and overall plant health.
4. Maturation and Growth Duration (C4)
   Evaluate the maturity and growth duration of the rice variety. Depending on the needs and growing conditions, choose seeds that have an appropriate growth duration, taking into account the length of the growing season and any specific requirements that is preferred.
5. Environmental Adaptability (C5)
   Consider the environmental conditions in the area, such as temperature, rainfall patterns, soil type, and altitude. Select rice seeds that are well-adapted to the specific environment to ensure optimal growth and yield.
6. Farmer Feedback and Performance (C6)
   Seek feedback from local farmers or agricultural experts who have experience with the rice seed variety. Consider their experiences, success stories, and recommendations to assess the variety's performance under local conditions.
7. Yield Potential (C7)

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Look for rice seeds that have a high yield potential, meaning they are capable of producing a significant quantity of rice grains per unit area. Consider the historical performance data and yield trials conducted for the seed variety to assess its productivity.

8. Grain Quality (C8)
   Assess the quality characteristics of the rice grains produced by the seed variety. Consider factors such as grain size, shape, color, aroma, texture, cooking quality, and taste. Select seeds that yield rice with desirable quality traits that are preferred by consumers or meet market demands.

Each of those criteria has 3 level, which reflects the minimum (1), middle (2) and maximum (3) score. Table 2 shows the pairwise comparison matrix of all of 8 criteria, which has CR = 0.91 so the consistency ratio is accepted. From the pairwise comparisons, we obtained the absolute weight of each criteria as follows (Table 3):

Table 2. The matrix of Pairwise Comparison

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
C1	1	9	3	3	9	9	9	9
C2	1/9	1	1	1	5	5	5	5
C3	1/3	1	1	3	9	9	9	9
C4	1/3	1	1/3	1	7	7	7	7
C5	1/9	1/5	1/9	1/7	1	1	3	3
C6	1/9	1/5	1/9	1/7	1	1	3	3
C7	1/9	1/5	1/9	1/7	1/3	1/3	1	3
C8	1/9	1/5	1/9	1/7	1/3	1/3	1/3	1

Table 3. The weight of each criteria

Criteria	**Weight (%)**	**Rank**
Seed Purity and Uniformity (C1)	40.6	1
Disease and Pest Resistance (C2)	12.3	4
Agronomic Traits (C3)	21.6	2

Maturation and Growth Duration (C4)	14.2	3
Environmental Adaptability (C5)	3.5	5
Farmer Feedback and Performance (C6)	3.5	5
Yield Potential (C7)	2.4	7
Grain Quality (C8)	1.8	8

Since the consistency ratio is accepted, then we continue to perform profile matching algorithm after obtaining weight for each criteria. Table 4 shows the value of each alternative, target value and the score which calculated using metrics presented in Table 2. For example, profile of Inpari 42 which has best resistance to pest and disease (value = 3), and the target value = 2. Therefore, the gap score is 3-2 = 1, which make the profile gap score, according to Table 2, is equal to 4.5.

Table 4. The gap profile of alternatives

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
Target	**1**	**2**	**2**	**1**	**3**	**2**	**3**	**3**
Inpari 42	1	3	2	2	0	1	1	3
Inpari 43	1	2	2	2	0	1	1	3
Inpari 45 Dirgahayu	2	2	1	1	0	1	1	2
Inpari 32	1	3	2	1	0	2	2	2
…	…	…	…	…	…	…	…	…
Gap Profile Score								
Inpari 42	5	4.5	5	4.5	2	4	3	5
Inpari 43	5	5	5	4.5	2	4	3	5
Inpari 45 Dirgahayu	4.5	5	4	5	2	4	3	4
Inpari 32	5	4.5	5	5	2	5	4	4
…	…	…	…	…	…	…	…	…

The final result of the profile matching procedure is a ranking of the submitted candidates for selecting the finest rice seedlings. Based on the values in table 4, the scoring values are arranged in Table 5 from highest to lowest final score.

Table 5. The final score and rank evaluation

Alternatives	**Final Score**	**Rank (by PMA)**	**Rank (by Experts)**
Mekonga	4.87	1	1
Inpari 32	4.79	2	2
Inpari 24	4.74	3	4
Inpari 43	4.74	4	3

Inpari 42	4.67	5	5
Sidenuk	4.62	6	6
Cimelati	4.59	7	9
IR.64	4.57	8	8
Pepe	4.57	9	7
Mapan P-05	4.48	10	10
Sunggal	4.41	11	11
Inpari 45 Dirgahayu	4.37	12	12
M70D	4.34	13	14
Padjadjaran Agritan	4.33	14	13
Sintanur	4.22	15	15
Kabir 05	4.20	16	16
Ciherang Janger	4.15	17	17
Raja Lele	4.05	18	18
Ciherang	4.01	19	19

To analyse the profile matching algorithm, we collected feedback from domain experts who have utilized the profile matching algorithm regarding their satisfaction, experiences, and any specific issues encountered. The recommendation or relevant matches from the experts also shown in Table 5. To compare the rank from the algorithm and relevant feedback from domain experts, we use Mean Absolute Percentage Error (MAPE). This method is commonly used to measure the accuracy of forecasts or predictions by comparing them to the actual values (Deina et al., 2023).

MAPE calculates the average percentage difference between the predicted values and the actual values, providing a relative measure of forecast accuracy. MAPE expresses the error as a percentage of the actual values. It represents the average magnitude of errors relative to the scale of the data. MAPE values closer to 0 indicate a smaller average percentage error, which indicates better accuracy and closer alignment between the predicted and actual values. On the other hand, higher MAPE values indicate larger errors and less accurate predictions. Based on the rank evaluation presented in Table 5, MAPE score = 6.5% which indicates lower error prediction.

Conclusion

From the study that has been done, we can take the following conclusions:

1. The decision support system for best rice seeds selection has been successfully put into place. The MAPE score shows that the error is relatively low.
2. According to the specified criteria, weights, and target values, the system provides users with recomen dation solutions.
3. The criteria, ranking criteria, and goal values for the system are all changeable, so it can be changed to meet the needs of farms.

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