Precision Agriculture Technology Evaluation using Combined AHP and GRA for Data Acquisition in Apiculture

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Abstract

Precision Agriculture has been experiencing an essential growth in the implementation of industrial internet of things based applications. The proposed evaluation framework uses a hybrid decision-making model for technology selection. The structure combines two extensively used methods, Analytic hierarchy Process (AHP) and Grey Relational Analysis (GRA). The evaluation process of data acquisition system features is two-fold. First, AHP is used to assign importance to the criteria. Next, GRA is used to assess the alternatives concerning the criteria. Finally, we obtain the final grey relational coefficients for each alternative and chose the most suitable one.

Keywords

Precision Agriculture, Apiculture, AHP, GRA

1. Introduction

Precision Agriculture continues rising importance over agriculture trends. The development of precision agriculture technologies arises from related topics like robotics, electronics, industrial internet of things and food security as their main goal. According to Keswani et al. [1] Precision agriculture is a tool that increases the farm potential, increment the income and reduces the environmental impact by automating entire farming methods. In recent years Precision Agriculture has become a relevant technology trend over industrial internet of things and Industry 4.0. Gebbers [2] gives a formal description, which shows that Precision agriculture involves a collection of technologies that include sensors, information support systems and devices to improve the return from variable and uncertain agricultural methods. It is possible to find many different applications related to precision agriculture and data acquisition technology [3, 4] . Among them, we highlight the study of how to classify the growth stage of potato crops [5], the discrimination of carrot and three weed species in the crop field. [6], the utilization of artificial intelligence and machine learning to detect, count and geo-locate

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plants, categorize them and predict yield and crop load [7], the collection of large data sets for a single corn plant [8], enhance energy efficiency [9], remote sensing using drones [10], climate change monitoring [11], detection of infections and crop classification [12], smart crop-field monitoring and automation of irrigation systems [13], the use of IoT devices for sensing the agricultural data and store data into the Cloud [14], the use of Data Mining Techniques and IOT to improve the crop yield [15], nutrient management for livestock [16, 17] and pollution-free cultivation systems among many others.

2. Literature review

Analytic hierarchy process is a decision-making tool whose main objective is to interpret the intangible judgments of people as tacit preferences. It does so by decomposing the problem into several hierarchical levels. The first level is the objective or goal, next, the comparison criteria and sub-criteria, and at last, the alternatives [18]. Using AHP brings advantages such as handling uncertain information lowering the experience of decision-makers. The AHP technique can be applied in many fields. Among them, we can highlight project selection, prioritization of environmental impacts[19], mining method selection [**?** 20], budget allocation, medical decision-making, transportation [21], manufacturing an supply chain [22, 23, 24] among many others.

Grey relation analysis is applied in multiple fields. Yeh [25] proposed an early combination with multi-criteria decision-making techniques in order to evaluate weapons systems. Later, other developments arise combining GRA with AHP in diverse areas including the selection of marketing networks [26], the impact analysis of damage in natural disasters [27] among others. A formal description of GRA and AHP is given by [28]; later Song and Jamalipour[29, 30, 31] extend the use of the AHP-GRA combination in the selection of networks in wireless communications, the same year Li also applies this combination in the selection of materials [32] and data transmission on demand. Zhang also implemented this combination in the evaluation of knowledge management tools [33], Han managed to apply this combination in maintenance [34] and Zhang in the optimization of the wastewater treatment process [35]. Zhao in the evaluation of courses [36]. [37] natural gas pipeline operation schemes, [38] Evaluation of tea crops [39] supplier evaluation More recent applications in agriculture that include the AHP-GRA combination can be seen at [40, 41, 42, 43, 44].

2.1. Analytic hierarchy process

For solving the Decision Making problem, we propose the use of AHP, as an accepted and used often in problems that include subjective judgments of people. According to Saaty [45, 18] the AHP is a useful tool to structure complex problems that influence multiple criteria and at the same time classify a set of alternatives in order of importance. Initially a hierarchical structure is made where the main decision problem is identified, then the criteria and sub-criteria that are taken into account for the decision are identified.The last level corresponds to the set of alternatives that will be evaluated concerning each of the criteria and sub-criteria. This evaluation is carried out through a series of binary comparisons in a matrix n x n, where n is the number of elements to be compared. In order to make the comparison, a scale is required.

Table 1
Saaty scale

Relative	Intensity Definition
1	Equal importance
3	Moderate importance of one element over another
5	Strong importance of one element over another
7	Very strong importance of one element over another
9	Extreme importance of one element over another

He proposed a scale between 1 and 9 where each intermediate value has an interpretation for the decision-maker (see Table **??**).

Values 2, 4, 6 and 8 are intermediate values that can be used in some cases. The next step is to find the relative priorities of the criteria and / or the alternatives. This step is based on the eigenvector theory. For example if a comparison matrix is A, then:

$$Aw = \lambda_{\max} w \tag{1}$$

Where w corresponds to the column vector of the relative weights obtained by making the average of each line of the normalized comparison matrix.

The value of $\lambda_{\max}$ is obtained by adding the column vector corresponding to the multiplication of the original comparison matrix with the column vector of relative weights.

$$\lambda \max = \sum_{i}^{n} Aw \tag{2}$$

Because comparisons are made subjectively, a consistency index is required to measure the consistency of the person making the ratings. The consistency index and the consistency ratio CR are calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \qquad CR = \frac{CI}{RI} \tag{3}$$

Where the RI inconsistency ratio is a comparison constant that depends on the size of the paired comparison matrix for sizes of n = 9 (our criteria x criteria matrix) RI = 1.45

2.2. Grey Relational Analysis

Grey relational space theory introduced by Deng Julong [46] is widely used to obtain the relations among the reference factors and other associated factors in a system.

Step 1. Generate the comparative factors. A set with n components of criteria can be expressed as $X_i' = \left(X_{i1}', X_{i2}', \ldots, X_{in}'\right)$, where X_{in}' means the jth criteria of X_i' . If all criteria are comparable, the m comparative factors can be expressed as:

$$X' = \begin{bmatrix} X_{11}' & X_{12}' & \cdots & X_{1n}' \\ X_{21}' & X_{22}' & \cdots & X_{2n}' \\ \vdots & \vdots & \cdots & \vdots \\ X_{m1}' & X_{m2}' & \cdots & X_{mn}' \end{bmatrix} \tag{4}$$

Step 2. Determine the reference series and normalize all data sets. Degree of relation can represent the relation of two series; therefore, an objective series called reference series shall be established and expressed as$X_0 = (X_{01}, X_{02}, \dots, X_{0n})$. Data sets can be treated using one of the following types: 'larger-is-better' or 'smaller-is-better'.

- In case of 'larger-is-better' data treatment $x_i(j)$, can be normalized into $x_i^*(j)$ The formula is defined as follows (5):

$$x_i^*(j) = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{5}$$

- In case of 'smaller-is-better' data treatment $x_i(j)$, can be normalized into $x_i^*(j)$ The formula is defined as follows (6):

$$x_i^*(j) = \frac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \tag{6}$$

Step 3. Compute the distance $\Delta_{0i}(j)$ between the reference series and the comparative series.

$$D_0 = \begin{bmatrix} \Delta_{11} & \Delta_{12} & \cdots & \Delta_{1n} \\ \Delta_{22} & \Delta_{22} & \cdots & \Delta_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \Delta_{m1} & \Delta_{m2} & \cdots & \Delta_{mn} \end{bmatrix} \tag{7}$$

where $\Delta_{ij} = \left\| X_{0j} - X_{ij} \right\|$.

Step 4. Calculate the grey relational coefficient γ_{ij} as follows:

$$\gamma_{ij} = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}}, \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{8}$$

where $\Delta_{\min} = \min\min\left(\Delta_{ij}\right), \quad \Delta_{\max} = \max\max\left(\Delta_{ij}\right)$, and ζ is an identifier $\zeta \in (0, 1)$ only affecting the relative value of risk without changing the priority. According to [46] generally $\zeta = 0.5$.

Step 5. Calculate the degree of grey relation based upon the γ_{ij} and the group weights of risk factor w_j, which is given as follows:

$$\Gamma_{ij} = \sum_{j=1}^{n} \bar{w}_j \gamma_{ij} \tag{9}$$

3. Methodology for combined AHP and GRA in Apiculture

In this section we show how the use of a model that combines AHP-GRA can help to manage qualitative and quantitative information in the selection of technology for data acquisition for the beekeeping sector. Beekeeping has particular characteristics necessary for proper performance of its hives, such as location, temperature, humidity, population control of the swarms, among others. The model was developed for a case in Colombia, located in the rural area of Carmen de Carupa. Which has a relative humidity of 86% and an average temperature of 10

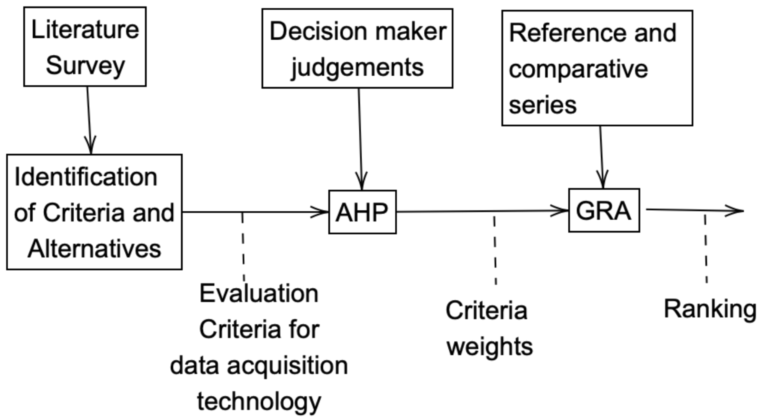

Figure 1: Methodology for combined AHP and GRA.

degrees Celsius. Next we will describe the Smart farming technologies, then we will describe the alternatives and the criteria of the model, finally we will apply the AHP-GRA combination in order to obtain the best alternative for the selection of data acquisition technology.

Smart farming technologies are classified into three principal classes that incorporate entire operation of Precision Agriculture:

- Data acquisition technologies: this class includes all surveying, mapping, navigation and sensing technologies.
- Data analysis and evaluation technologies: this class includes from computer-based decision models to complex farm management and information systems.
- Precision application technologies: this class contains all application technologies.

In order to evaluate data acquisition technologies. First, we determine alternatives and criteria from an extensive literature survey, next we apply AHP in order to obtain the weights for all criteria. At last, we apply grey relational analysis to rank all alternatives and select the most suitable one. An schema of the evaluation process can be seen in Fig. 1 as follows:

3.1. Technology Alternatives for Precision Agriculture

- **Global Navigation Satellite Systems:** is the conventional name for satellite navigation systems that contribute independent geo-spatial positioning with global coverage.
- **LiDAR Sensors:** Light Detection and Ranging are instruments that measure the distance from the target by laser.

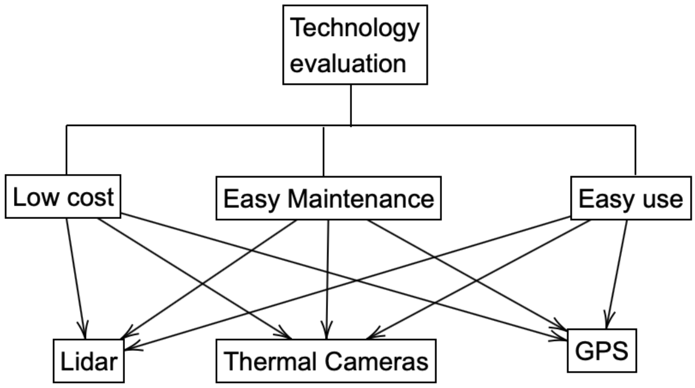

Figure 2: AHP hierarchical model.

- **Thermal Cameras Systems:** Thermal cameras have the ability to generate images related to the ambient temperature.

3.2. Evaluation Criteria

Many factors need to be considered in the selection of perception sensors and other technologies in agriculture, which are described below:

- **Easy Maintenance:** Reliability is essential for perception-based applications. Sensor performance will quickly degrade when exposed to harsh agricultural environments, and frequent sensor maintenance is required. The ease of sensor maintenance is another consideration in selecting a perception sensor.
- **Low Cost:** The cost is one of the most important factors that influence, since in some cases the farmer cannot have access to high-cost elements that allow him to follow up on bees or any type of food that he sows on his farm.
- **Easy to Use:** The simple and fast use of the measuring instruments used in Precision Agriculture is essential when acquiring them, since some farmers do not know how to read or write, therefore a friendly technology is needed for them.

3.3. AHP hierarchy and determination of relative weights of all criteria

From the literature review, the alternatives and criteria most related to our case study are established and we build the hierarchy that can be seen in the figure 2 as follows.

Table 2
Weights of the evaluation criteria

	Easy maintenance	Easy use	Low cost
Weight	0.73064	0.18839	0.08096
Rank	1	2	3

Table 3
Qualitative and quantitative data

	Easy maintenance	Easy use	Low cost
Lidar	2	4	100
Thermal Cameras	6	5	300
GPS	6	8	150

AHP is used to determine the relative weight of each criterion. using the scale from 1 to 9 with different levels of importance proposed by saaty. The priorities are calculated by calculating the dominant eigenvector that belongs to the matrix of pairwise comparisons for the criteria. The consistency ratio of the matrix of even comparisons corresponding to the criteria is CR=0.06239. Te weights of all criteria can be seen in Table 2 as follows.

3.4. Usage of GRA to establish the best technology for data acquisition

The qualitative and quantitative evaluations are added in the table below, the criteria $j = \{1, 2\}$ are qualitative. On the other hand, the criterion $j = 5$ is quantitative and corresponds to the price in dollars of each item.

Step 1. Generate the referential series and the compared series.

$$X_i = \begin{pmatrix} 2 & 4 & 100 \\ 6 & 5 & 300 \\ 6 & 8 & 150 \end{pmatrix}$$

Step 2. Then the referential series of $x_0 = \{6, 8, 100\}$, and the compared series of $x_1 = \{2, 4, 100\}$, $x_2 = \{6, 5, 300\}$, and $x_3 = \{6, 8, 150\}$.

Step 3. Calculate the distance between the referential series and the compared series.

$$D = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 0.75 & 1 \\ 0 & 0 & 0.25 \end{pmatrix}$$

Step 4. Calculate the grey relational coefficient

$$\gamma_{i,j} = \begin{pmatrix} 0.3333 & 0.3333 & 1.0000 \\ 1.0000 & 0.4000 & 0.3333 \\ 1.0000 & 1.00000. & 6667 \end{pmatrix}$$

Table 4
Calculation results

	Easy maintenance	Easy use	Low cost
Weights	***0.73064***	***0.18839***	***0.08096***
Lidar	0.333333333	0.333333333	1
Thermal Cameras	1	0.4	0.333333333
GPS	1	1	0.666666667

Step 5. Calculate of the degree of the grey coefficient. the grey coefficient can be seen in Table 4 as follows:

The final grey relational coefficients for every alternative are: $\Gamma_{01}(\text{Lidar}) = 0.387303333$, $\Gamma_{02}(\text{Thermal} - \text{cameras}) = 0.832982667$, $\Gamma_{02}(\text{GPS}) = 0.973003333$ The priorities of the three potential technologies (in order with their grey relational grades) is GPS > Thermal cameras > Lidars.

4. Conclusions

In this article, the combined AHP and GRA procedure gives a solution, including quantitative and qualitative information. This coordinated approach has selected the technology based on the proposed evaluation model. The benefit with this approach is that it is quite adapted to deal with problems that involve qualitative and quantitative values, and enables the evaluation based on limited information.

Based on the result obtained in the model, we can conclude that the best technology to acquire data in apiculture is GPS. It will help to obtain a useful mapping of the terrain with an adequate angle and temperature for giving the right conditions to the development of bees population.

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