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Agricultural Tractor Selection: A Hybrid and Multi-Attribute Approach

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Abstract: Usually, agricultural tractor investments are assessed using traditional economic techniques that only involve financial attributes, resulting in reductionist evaluations. However, tractors have qualitative and quantitative attributes that must be simultaneously integrated into the evaluation process. This article reports a hybrid and multi-attribute approach to assessing a set of agricultural tractors based on AHP-TOPSIS. To identify the attributes in the model, a survey including eighteen attributes was given to agricultural machinery salesmen and farmers for determining their importance. The list of attributes was presented to a decision group for a case of study, and their importance was estimated using AHP and integrated into the TOPSIS technique. In this case, one tractor was selected from a set of six alternatives, integrating six attributes in the model: initial cost, annual maintenance cost, liters of diesel per hour, safety of the operator, maintainability and after-sale customer service offered by the supplier. Based on the results obtained, the model can be considered easy to apply and to have good acceptance among farmers and salesmen, as there are no special software requirements for the application.

Keywords: agricultural modernization; investment in tractors; multicriteria and multi-attribute selection models

1. Introduction

Usually, quality, service and cost are attributes associated with the product manufacturing sector; however, for agricultural products, these attributes, as well as government regulations are stricter, and compliance constitutes a strategic objective continuously pursued by agribusiness and small farms in Western Mexico on their way to participate in current dynamic and globalized market environments [1,2]. These small businesses have several options to achieve goals related to quality, cost and delivery time, among other performance indexes, but one of the most used strategies consists of investing in advanced technology (AT), which often includes tractors. These are usually acquired, so that they can be implemented in agricultural production systems, processing lines and industrialization activities [3–5].

Frequently, having decided to invest in AT, e.g., a tractor, managers or owners face additional problems. Since there are many alternatives (tractors) currently available on the market (brand names), many attributes that characterize them and many evaluation techniques of these alternatives [6,7] create a confusing situation for them due to the complex decision making problem.

In relation to the purchasing options for farmers interested in AT or tractor investment in Mexico, there are distributors of foreign technology, which offer several advantages according to the vast topography of the country.

Regarding attributes that characterize tractors, these can be objective and subjective. Objective attributes are usually measured in terms of numbers and represent costs and engineering characteristics of the evaluated technology, and these are usually also called quantitative or tangible attributes. These include initial cost, energy consumption (diesel, lubricants) and maintenance cost, among others. Usually, these kinds of attributes are provided by technology suppliers. On the other hand, subjective attributes refer to intangible or qualitative information and must be integrated into the evaluation process due to their relevance in decision making. In the process of selecting a tractor, the most important subjective attributes are those related to quality customer service and safety. Besides, determination and evaluation of these kinds of attributes require expert judgment based on experience and are generally expressed by means of a Likert scale [8–10].

Regarding evaluation techniques for the selection of the best option in technology, these can be classified into economic, strategic and analytical [11]. Economic techniques (ET) are commonly used in industrial and agricultural practice; however, they have been criticized by authors for not integrating qualitative attributes into their analysis, and said models are considered reductionist, as they cannot represent the entire investment problem and technology selection. Some examples of these techniques are the net present value (NPV), internal rate of return (IRR) and equivalent uniform annual cost, pay back (PB) and cost/benefit analysis.

Strategic techniques (ST) are based on the company's goals and mission, but criticized for not including economic aspects in the evaluation, and although they are widely used by senior and CEO (Chief Executive Officer) management in companies, they often cannot, however, be interpreted and understood by people from lower positions in the organizational farm structure. Some of these ST are sacred cows, technical specifications and government alignment, among others.

Finally, analytical techniques are little known owing to their recent application in industry in comparison to other techniques. They also present the advantage of integrating alternative economic, strategic, social and technological attributes into the evaluation process, so their use is highly recommended in situations where a significant number of qualitative and quantitative attributes need to be evaluated. Among these techniques are the analytical hierarchy process (AHP) [12], dimensional analysis (DA) [13], technique for order preference by similarity to the ideal solution (TOPSIS) [14] and the linear additive model (LAM) [15]. In addition, analytical techniques allow groups of participants to make decisions together, adding consensus to the evaluation process.

Industrial application of these technology evaluation techniques is widely reported in the literature, although mainly applied to manufacturing technology; cases applied to agricultural technology are very few.

In the manufacturing field, some authors have proposed an economic method incorporating various costs into the evaluation of robots [16], while others have proposed computer-aided methods to account for industrial manipulators [17,18]. In addition, some authors have proposed goal programming techniques for the selection of technology applied to manufacturing cells [19], while other authors have developed an expert system for selection and evaluation of robots [20], and recently, some TOPSIS-based models have been proposed to evaluate a set of robots [21].

On the subject of the application of quantitative techniques in the evaluation of AT applied to agriculture, there is a stochastic simulation to evaluate forage crushing machinery [22], equations for investment in machinery based on the provision of land and infrastructure [23] and a nonlinear model to determine the investment limit in agricultural mechanization processes [24]; however, in [25] appears a mixed integer linear programming model for evaluating agricultural machinery, and recently, [26] proposed a model for site selection. However, previous assessments only used quantitative attributes in the evaluation process, neglecting qualitative characteristics of advanced technology in agriculture (ATA).

The implementation of multi-attribute techniques in decision making and technology selection in agriculture is scarcely reported in the literature. For example, there is an analysis of how water policies impact agricultural practices [27], evaluation for irrigation system designs and evaluation [28] and a multi-attribute approach and linear programming for risk aversion investments in agriculture [29]. Recently, a non-interactive elicitation method for non-linear multi-attribute utility functions analyzing their application in agricultural economics was proposed [30]. Other recent multi-attribute research can be consulted in [31,32] for utility analysis for policy selection and financing the preservation of forests, as well as a sustainable optimization model for agricultural production.

Problem Research and Objectives

Based on the foregoing and different approaches that have been related to investment in technology, we can say that this is a complex problem, neither defined nor structured, and traditional approaches (usually quantitative) used in investment analysis are only considering operational and economic attributes from technologies, ignoring qualitative attributes in the evaluation process. Specific references related to agricultural or farm technologies are also very few.

Furthermore, on occasion, the models proposed in agriculture are too complex for the farmers to understand: advanced mathematical knowledge may be required, as well as the use of special software, and investment in farm machinery is not a frequent task, making it difficult to invest in special software. As a result, farmers usually hire consultants, who are not always fully aware of the investment problems for the farmer, the company's needs or special requirements.

Additionally, in Mexico, farmers integrate associations or rural production cooperatives for facing the limited availability of land and always join efforts in high investments, such as tractors, which are shared among them, following a schedule, and this allows for better use of technical resource usage.

Therefore, this research proposes a multicriteria and multi-attribute model that allows the most important attributes to be integrated into the tractor evaluation process, but also the farmers' own opinions for the weighting process of the aforementioned attributes. The model is based on AHP and TOPSIS, techniques that can integrate both objective and subjective technological attributes in a tractor. TOPSIS is easy to understand for farmers, as it is based on the concepts of distances, usually learned at high school, and is resolved completely in Excel, software available on almost every computer, saving on specialized software investment. In this manner, the farmers in the rural cooperative are able to assess without the need of an expert consultant and combining all of their requirements and needs into an integrative model.

2. Materials and Methods

In a multicriteria evaluation, the first step is to determine which attributes will be included in the evaluation followed by an evaluation of a set of alternatives to make the decision. The following activities were carried out to reach the objective: to choose one tractor out of many.

2.1. Tractor Characterization

The first step in this work was to design a questionnaire identifying the attributes that characterize farm tractors by reviewing existing literature and interviewing farmers and machinery salespersons adopting some characteristics and attributes from AMT, as proposed in [9,10]. The initial questionnaire consisted of eighteen attributes that were obtained from literature reports and validated by academics, farmers and machinery sellers for a better understanding of the process and context adaptation. The questionnaire was divided into two sections: the first section aimed to obtain demographic information related to responders, and the second section contained the list of eighteen attributes grouped into five generic categories as regards cost, technical specifications, customer service, quality and safety of the operator.

2.2. Questionnaire Application and Validation

The questionnaire was submitted to farmers, machinery salespersons and academics in Mexico, using a Likert scale from one to nine to answer the questionnaire with the most common attributes, where one represents null importance of the attribute and nine the maximum importance when farmers are buying a new tractor [33].

To carry out the survey, we visited several governmental agencies where farmers perform some kind of administrative paperwork, such as SAGARPA (Ministry of Agriculture, Livestock, Rural Development, Fisheries and Food) and SEDER (Ministry of Rural Development), and in the case of ATA vendors, the applicants are visited at their business address.

Information was processed and logged using the statistical software SPSS 21[®] (IBM, New York, NY, USA) and MS Office Excel[®] (Washington, DC, USA) for a descriptive analysis. In addition, tests were performed to detect missing values, and since the data contained in the surveys was on an ordinal scale (Likert scale), missing values were replaced by the median [34]. In addition, tests were performed to identify extreme values or “outliers” by standardizing the data and only considering a value extreme if the standardized absolute value was greater than four [34,35].

Following the screening process, a statistical validation was conducted using Cronbach’s alpha index (CAI), with a minimum cut-off value of 0.7 [36]. Moreover, at this stage, some tests were performed to increase reliability, so the removal was considered of some attributes contained in every analyzed dimension to assess whether reliability can be increased [37].

2.3. Descriptive Analysis

With a screened and validated database, some descriptive parameters were obtained. As a central tendency measure, the median was calculated because the data represented values in an ordinal scale. Furthermore, as a dispersion measure, the interquartile range was obtained, being the difference between the third and first quartile [37]. This analysis helped determine the importance given by farmers to each attribute and the dispersion or concordance among them from a univariate point of view.

An attribute with a high median value indicates that the attribute is very important for the surveyed participants, and low values indicate that the attribute is not that important. Similarly, a low value in the interquartile range indicates that the surveyed participants show significant concordance and consensus regarding the real value of the attribute, but high values indicate a high level of dispersion and absence of consensus.

2.4. The Proposed Model

The proposed model integrated two techniques, AHP and TOPSIS. The former was used to weight the attributes and the latter to compare the alternatives. Using the most important attributes established in a list, for every application of the evaluation in the farmers’ associations, the decision group determined the attributes for their own selection problem. A lack of coincidence is common when evaluating the same set of attributes, since each group of farmers has different needs. Having identified attributes for each decision group, the next task is to explain the AHP technique, which can be summarized as follows.

2.4.1. Analytic Hierarchy Process

AHP is a technique developed by Thomas Saaty in 1980, belongs to the family of multicriteria and multi-attribute techniques [38] and decomposes a complex problem into hierarchies, and each level is broken down into specific elements [39]. The main goal of the analysis is placed on the first level; attributes, sub-attributes and decision alternatives are listed in lower levels of the hierarchy. AHP analyzes the attributes in the decision process without requiring a common scale.

AHP is based on pairwise comparisons, generating a decision matrix and making evaluations in accordance with a scale that appears in Table 1. The pairwise comparison of element i with element j is placed at the position a_{ij} in matrix A of paired comparisons, as shown in (1). The reciprocal values of these comparisons are placed in the position a_{ji} in A , in order to preserve the consistency of the judgment.

Table 1. Saaty's scale.

Value	Definition
1	Equal importance
2	Weak
3	Moderate importance
4	Moderate plus
5	Strong importance
6	Strong plus
7	Very strong
8	Very strong plus
9	Extreme importance
Reciprocals of above	If attribute i has one of the above non-zero numbers assigned to it when compared to attribute j , then j has the reciprocal value when compared to i

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{n1}} & \frac{1}{a_{n2}} & \dots & 1 \end{bmatrix} \quad (1)$$

According to [40], once pairwise comparisons have been made, the selection problem is reduced to the estimation of eigenvalues and eigenvectors, which represent the priorities and the consistency index in the assessment process, respectively. Usually, we have:

$$A \times w = \lambda_{\max} \times w \quad (2)$$

where:

- A = reciprocal pairwise comparisons matrix;
- w = eigenvector for the maximum eigenvalue in A ;
- λ_{\max} = maximum eigenvalue in A .

A benefit obtained when using AHP is that this technique allows one to identify and consider the inconsistencies of the decision makers, as they are rarely consistent in their judgments of qualitative factors, and there are some indexes for measuring information validity, such as the consistency index (CI) and consistency ratio (CR) to measure the quality of a decision maker's judgments [41]. A CR value lower than 0.10 is considered acceptable. The CI and CR can be estimated using Equations (3) and (4), where λ_{\max} is the maximum eigenvalue for the pairwise comparison matrix and n is the number of attributes evaluated.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

$$CR = \frac{CI}{AI} \quad (4)$$

The CR index is a function that depends on AI and CI , where AI represents a random index. Thus, CR is a measure of the error incurred by a decision maker, where it must be less than 10% of the random index (AI). Table 2 shows the values for AI for 3 to 10 attributes.

Table 2. Random indexes.

Matrix Size	3	4	5	6	7	8	9	10
AI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

However, if a decision group is analyzing a problem, their judgments must be combined in a unique pairwise comparison matrix, and to solve this problem, [42] suggests that the geometric mean can be used as the average of judgments values for this matrix; see Equation (5).

$$a_{ijT} = (a_{ij1} \times a_{ij2} \times a_{ij3} \times \dots \times a_{ijn})^{1/n} \quad (5)$$

Currently, there is special software available on the market that has integrated the AHP routine, but in this paper, we have used the geometric mean estimation for attributes' weight estimation, because it can be calculated using any spreadsheet [43].

2.4.2. Matrix Approach in Multi-Attribute Assessment

To generalize, we shall assume that there are K tractors and that the best must be selected by a decision group. The alternatives are denoted as A^1, A^2, \dots, A^K . However, in multi-attribute assessment, two different kinds of attribute are integrated: qualitative (subjective) and quantitative (objective), which are defined as follows:

Objective and Subjective Attribute Determination

To generalize, we shall assume that there are J objective attributes and L subjective attributes that have been identified in a set of tractors. The J objective attributes are denoted by X_1, X_2, \dots, X_J and the L subjective attributes by $X_{J+1}, X_{J+2}, \dots, X_{J+L}$ [14]. The method to determine these attributes is explained in the following paragraphs.

Objective Attribute Values Matrix

The objective attribute values matrix for the selection process was obtained from the tractors' manufacturers and refers to aspects associated with costs and engineering characteristics. In this study, values are represented as a matrix of objective values (OV). Equation (6) displays that matrix.

$$OV = \begin{matrix} A^1 \\ A^2 \\ \vdots \\ A^k \end{matrix} \begin{bmatrix} X^1_1 & X^1_2 & \dots & X^1_J \\ X^2_1 & X^2_2 & \dots & X^2_J \\ \vdots & \vdots & \ddots & \vdots \\ X^k_1 & X^k_2 & \dots & X^k_J \end{bmatrix} \quad (6)$$

where X^k_j is the value for attribute j and alternative k , for $k = 1, \dots, K$ and $j = 1, \dots, J$.

Subjective Attribute Values Matrix

The values for subjective attributes in the selection process of tractors were obtained from experts' assessments. In this case, the experts were farmers and participants involved in investment processes. To generalize, assume that there are P farmers constituting a decision group to evaluate the AT according to subjective attributes. They expressed their judgments using a scale from 1 to 9, in which 1 means that the attribute is absent in an alternative, and 9 means that the attribute is present. Each farmer builds a matrix with subjective values (SV) as indicated in Equation (7), and finally, there must be P matrixes, one for each farmer.

$$SV^P = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_K \end{matrix} \begin{bmatrix} X_{J+1}^{1P} & X_{J+2}^{1P} & \cdot & \cdot & X_{J+L}^{1P} \\ X_{J+1}^{2P} & X_{J+2}^{2P} & \cdot & \cdot & X_{J+L}^{2P} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ X_{J+1}^{KP} & X_{J+2}^{KP} & \cdot & \cdot & X_{J+L}^{KP} \end{bmatrix} \quad (7)$$

The SV^P P matrices provided by farmers were added term by term to generate a total subjective values matrix, in which each one of its elements is divided by the value of P (number of farmers), to obtain an arithmetic mean value that represents the groups' judgment; however, we assume that the P experts are rational in their judgment. Thus, the total subjective values matrix, which we will call TSV , is determined by Equation (8).

$$TSV = \sum_{P=1}^P SV^P / P = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_K \end{matrix} \begin{bmatrix} X_{J+1}^1 & X_{J+2}^1 & \cdot & \cdot & X_{J+L}^1 \\ X_{J+1}^2 & X_{J+2}^2 & \cdot & \cdot & X_{J+L}^2 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ X_{J+1}^K & X_{J+2}^K & \cdot & \cdot & X_{J+L}^K \end{bmatrix} \quad (8)$$

where $x_{J+i}^k = \frac{\sum_{p=1}^P x_{J+i}^{kp}}{P}$ for $k = 1, \dots, K$, $i = 1, \dots, L$ is the mean score of P experts for the A^k alternative with respect to the X_{J+i} attribute.

Final Decision Matrix

For the decision making problem, the final decision matrix (**FDM**) is constructed by combining matrices **OV** and **TSV**, as shown in Equation (9). Every line or row in **FDM** represents a tractor, and every column represents an attribute to be evaluated.

$$FDM = [OV, VST] = \begin{matrix} A^1 \\ A^2 \\ \vdots \\ A^K \end{matrix} \begin{bmatrix} x_{J+1}^1 & \dots & x_J^1 & x_{J+1}^1 & \dots & x_{J+L}^1 \\ x_{J+1}^2 & \dots & x_J^2 & x_{J+1}^2 & \dots & x_{J+L}^2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{J+1}^K & \dots & x_J^K & x_{J+1}^K & \dots & x_{J+L}^K \end{bmatrix} \quad (9)$$

The final decision matrix obtained is the base of the analysis. As this proposal for the evaluation of AT applies the TOPSIS technique, the TOPSIS methodology is described in the following sections.

2.4.3. TOPSIS Technique and Its Methodology

According to TOPSIS, during the selection process, an alternative A^k is considered a vector in a Euclidian space, as shown in Equation (10).

$$A^i = (x_1^i, \dots, x_{J+L}^i) \text{ for } i = 1, 2, \dots, k \quad (10)$$

Since each alternative in rows corresponds to a point in the $J + L$ -dimensional space (J objective attributes and L subjective attributes), in the same manner, the X -th attribute in columns can be analyzed as a vector in a k -dimensional space (k alternatives) given by Equation (11).

$$X_n = (x_n^1, \dots, x_n^k) \text{ for } n = 1, 2, \dots, J + L \quad (11)$$

The TOPSIS technique starts with the assumption that a better or worse alternative exists, usually called the ideal solution alternative (ISA) and anti-ideal solution alternative (AISA). The ideal solution

alternative is generated from the best nominal attributes values in every attribute, as shown in Equation (12).

$$A^+ = (x_1^+, x_2^+, \dots, x_{J+L}^+) \quad (12)$$

Likewise, the anti-ideal solution or anti-ideal alternative is generated from the worst values in each attribute and is given by Equation (13).

$$A^- = (x_1^-, x_2^-, \dots, x_{J+L}^-) \quad (13)$$

As every alternative is considered a point in a $J + K$ -dimensional space, an intuitive solution to the selection problem is to select the alternative that has the least Euclidian distance to the ideal alternative, and consequently, the selected alternative will be very similar to the ideal solution alternative. Another option for the best alternative is to select the alternative that is farthest from the anti-ideal solution alternative; but TOPSIS is a technique that integrates both distances, the distance to the ideal solution alternative and the distance to the anti-ideal solution alternative, and is presented in the next paragraph.

The TOPSIS methodology consists of the following three steps:

- (1) As some attributes are usually expressed in different scales or measurement units (\$, dollars for cost; m/s, meter by seconds for speed; kg, for load capacity; *etc.*), the first task in TOPSIS is to normalize each attribute X_n vector and convert them to TX_n following Equation (14). Thus, the values will be dimensionless.

$$TX_n = \frac{X_n}{||X_n||} = \left(\frac{x_n^1}{||X_n||}, \dots, \frac{x_n^k}{||X_n||} \right) \quad (14)$$

where $||X_n||$ represents the Euclidian norm for the attribute (vector magnitude) and can be obtained using Equation (15).

$$|X_n| = \sqrt{\sum_{i=1}^x x_i^2} \quad (15)$$

Sometimes, it is preferable to work directly with the alternatives, applying the normalization process using Equation (16). Furthermore, the ideal and anti-ideal solution alternatives must be normalized, according to Equations (17) and (18).

$$TA^k = (t_1^k, \dots, t_n^k) = \left(\frac{x_1^k}{||X_1||}, \dots, \frac{x_n^k}{||X_n||} \right) \quad (16)$$

$$TA^+ = (t_1^+, \dots, t_n^+) = \left(\frac{x_1^+}{||X_1||}, \dots, \frac{x_n^+}{||X_n||} \right) \quad (17)$$

$$TA^- = (t_1^-, \dots, t_n^-) = \left(\frac{x_1^-}{||X_1||}, \dots, \frac{x_n^-}{||X_n||} \right) \quad (18)$$

- (2) According to Equations (19) and (20), calculate the existing weighted Euclidian distances between the points represented by each alternative and those represented by the ideal and anti-ideal alternatives.

$$\rho(A^k, A^+) = ||w \times (TA^k - TA^+)|| \quad (19)$$

$$\rho(A^k, A^-) = ||w \times (TA^k - TA^-)|| \quad (20)$$

Here, w represents the attributes' weight obtained using AHP by the geometric mean method.

- (3) Sort the alternatives according to their distance from the ideal and anti-ideal solutions, as given by Equation (21).

$$RC(A^+, A^i) = \frac{\rho(A^k, A^+)}{\rho(A^k, A^+) + \rho(A^k, A^-)} \quad (21)$$

The selection criteria used in TOPSIS consists of selecting an alternative that includes the lowest values for $RC(A^k, A^+)$.

3. Results

Results are shown in two subsections, the analysis of data collected through the questionnaires and the TOPSIS application.

3.1. Sample Description

After two months surveying farmers, 416 valid questionnaires were received for the evaluation of eighteen attributes evaluated for tractor investment. Table 3 illustrates the sample description for each farmer's harvest and land availability; however, farmers only reported their main harvest, as sometimes, there were mixed harvests, e.g., coconut and banana planted on the same land, or the same farmer has more than one crop with a low quantity of hectares.

Table 3 lists (in descending order according to farmers' harvests) corn, banana and lemon harvests represented by 278 farmers with only three harvests, representing 66.82% of the sample. These products are typical of the surveyed region on the Mexican coast. According to land availability per farmer, they are in a range of five to 20 hectares, representing 45.67%.

Table 3. Sample description.

Crops	Land Availability for Main Crop					Total
	<1 Ha	1 to 5 Ha	5 to 20 Ha	20 to 50 Ha	>50 Ha	
Corn	0	10	65	28	5	108 (25.96%)
Banana	0	19	39	29	5	92 (22.12%)
Lemon	1	21	43	11	2	78 (18.75%)
Alfalfa	8	12	19	11	0	50 (12.02%)
Flowers	12	15	1	0	0	28 (6.73%)
Coconut	0	2	5	9	1	17 (4.09%)
Sugarcane	2	4	8	1	0	15 (3.61%)
Sorghum	0	2	3	4	2	11 (2.64%)
Wheat	0	3	5	0	2	10 (2.40%)
Oat	2	1	2	1	1	7 (1.68%)
Total	25 (6.1%)	89 (21.39%)	190 (45.67%)	94 (22.59%)	18 (4.33%)	416 (100%)

3.2. Descriptive Analysis of Attributes

Results of the descriptive analysis are shown in Table 4 for every attribute in tractors, sorted in descending order according to the median, which also presents the first and third quartile, as well as the interquartile range. The first three attributes are related to economic factors (initial cost, cost of energy consumption and annual maintenance cost), but the following two factors are related to the tractors' adaptability (number of tools to adapt and the availability of spare parts), and this means that farmers are seeking a low cost tractor, but with the capacity to handle many parts that can be adapted and integrated into the same tractor.

Table 4. Attributes' descriptive analysis.

Attribute Description	Median	25th Percentile	75th Percentile	IR
Initial cost	8.47	8.40	8.70	0.30
Cost of energy consumption	8.41	8.15	8.88	0.73
Annual maintenance cost	8.35	7.90	8.55	0.65
Number of tools to adapt (adapted)	8.25	7.78	8.37	0.59
Availability of spare parts	8.23	5.89	6.35	0.46
Availability of customer service	8.22	8.00	8.71	0.71
Flexibility of attachments	8.21	8.03	8.53	0.50
Engine power	8.16	7.69	8.47	0.78 ‡
Maintainability	8.12	7.67	8.42	0.75
Quality customer service	8.03	7.83	8.08	0.26 *
Variety of attachments available	7.96	7.91	8.02	0.10 *
Expandability	7.95	7.88	8.40	0.52
Cost of parts	7.84	7.45	8.02	0.57
Safety maneuver	7.16	6.85	7.63	0.77 ‡
Brand name	7.09	6.81	7.42	0.61
Comfort to maneuver	7.06	6.63	7.28	0.65
Safety when performing maintenance	6.33	5.89	6.81	0.91 ‡
Tractor model	6.17	6.05	6.25	0.21 *

* Low values in IR; ‡ high values in IR.

Regarding attributes occupying the last positions in Table 4, two groups of attributes can be observed. The first relates to manufacture prestige (brand name and tractor model), but the second group is worrying, as it relates to safety (operator's safety, comfort of operator, safety when performing maintenance), and that means that farmers give little importance to trademarks and their safety.

Besides, analyzing the interquartile ranges, low values in *IR* are represented by an asterisk, which indicates that there is a consensus on the real value for that attribute. This work is related to quality customer service, variety of attachments available and tractor model. Low median values and low *IR* values in "tractor model" indicate that farmers are not interested in trademarks and after-sale services from suppliers. In relation to attributes with high *IR* values, represented by (‡) in Table 4, these are related to "engine power", "safety maneuver" and "safety when performing maintenance"; that means that there is no consensus regarding the real value for that median, and that is because on interpreting the only median, safety presented low *IR* values; in other words, some farmers had high assessments for safety, while others had low values.

3.3. A Numerical Example

A tractor evaluation was executed using the AHP-TOPSIS hybrid technique, and the attributes analyzed are described in the next paragraph:

- Initial cost of the tractor (IC, \$), representing the amount of money, expressed in Mexican pesos, that the rural cooperative must pay if they get the tractor in a single instalment. The minimum value of this attribute is desirable.
- Rated power (RP, HP), representing engine power. This attribute is expressed in horsepower (HP), and the maximum value is desirable.
- Number of cylinders (NC), representing the number of cylinders in the engine. This value is expressed with a crisp value, and minimum values are desirables, because they are associated with diesel consumption.
- Displacement (DI, cm³) is the volume swept by all of the pistons inside the cylinders of an internal combustion engine in a single movement from top dead center (TDC) to bottom dead center (BDC). This value is expressed in cubic centimeters, and minimum values are desirable.

- Safety of the operator when maneuvering the tractor (SO), representing a subjective value that indicates the decision maker's assessment regarding the operator's safety. Maximum values are desirable.
- After-sale customer service from suppliers (CS), representing a subjective value that indicates the decision maker's assessment regarding services they feel they will obtain from suppliers following the purchase of the tractor. In this attribute, maximum values are desirable.

Note that the first four attributes are quantitative and can be expressed by certain measurement units provided by the tractor supplier, but the last two are qualitative. The decision group was integrated by five farmers from a rural cooperative with 47 members that have 842 land hectares available.

3.3.1. Weighting the Attributes: AHP Stage

Once the attributes have been defined by the decision group, then the next task is to obtain their weight using AHP. The weights of all attributes appear in the last row in Table 5.

Table 5. Final decision matrix.

A ^k	Attributes					
	IC	RP	NC	DI	SO	CS
A ¹	* 748,223	80	‡ 4	4530	‡ 8.8	‡ 8.6
A ²	520,730	* 75	‡ 4	4500	7.3	7.3
A ³	‡ 425,232.50	80	‡ 4	4070	* 6.2	* 5.3
A ⁴	649,477.50	100	* 6	* 6000	7.3	6.2
A ⁵	585,305	95	‡ 4	‡ 4000	8.2	8.3
A ⁶	702,590	‡ 110	* 6	* 6000	8.6	8.5
A+	425,232.50	110	4	4000	8.8	8.6
A-	748,223	75	6	6000	6.2	5.3
Optimization	Min	Max	Min	Min	Max	Max
W _i	0.23857	0.08151	0.10869	0.11593	0.07696	0.37834

‡ Best values according to the optimization criteria for an attribute. * Worst value according to the optimization criteria for an attribute.

3.3.2. Alternatives' Evaluation: TOPSIS stage

Due to space limitations, the estimation process for subjective attributes has been omitted. The final decision matrix appears in Table 5, where the last two rows illustrate alternatives A+ and A- and the optimization criteria for every attribute. Thus, the ideal tractor for a decision group of five farmers must have an initial cost (IC) of \$425,232.50 from A³, a rated power (RP) of 110 H.P from A⁶, with four cylinders (NC) from A¹, A², A³ and A⁵, a displacement of 4000 cm³ from A⁵, operator's safety of 8.8 from A¹ and, finally, an after-sale customer service of 8.6 from A¹; note that the best values are indicated with the ‡ symbol. The worst tractor for farmers is that which has an IC of \$748,223 from A¹, a rated power (RP) of 75 HP from A², with six cylinders (NC) from A⁴ and A⁶, a displacement of 6000 cm³ from A⁴ and A⁶, operator's safety of 6.2 from A³ and, finally, an after-sale customer service of 5.3 from A³; note that the best values are indicated with the * symbol. Observe that in an alternative represented by A¹, there are three attributes that belong to the ideal alternative.

Table 6 illustrates the normalized values of the attributes, obtained from Equations (10), (11) and (12). Furthermore, the last line presents the Euclidean norms of every attribute.

Table 6. Normalized values.

A^k	Attributes					
	IC	RP	NC	DI	SO	CS
A^1	0.4966	0.3594	0.3430	0.3758	0.4615	0.4699
A^2	0.3456	0.3369	0.3430	0.3733	0.3828	0.3989
A^3	0.2822	0.3594	0.3430	0.3376	0.3251	0.2896
A^4	0.4311	0.4492	0.5145	0.4977	0.3828	0.3388
A^5	0.3885	0.4268	0.3430	0.3318	0.4300	0.4535
A^6	0.4663	0.4942	0.5145	0.4977	0.4510	0.4645
A^+	0.2822	0.4942	0.3430	0.3318	0.4615	0.4699
A^-	0.4966	0.3369	0.5145	0.4977	0.3251	0.2896
Norm	1,506,604.043	222.598	11.662	12,055.530	19.070	18.301

Since each attribute has a different weighting or level of importance for the group decision, it was multiplied by the attribute weight that is in the normalized final decision matrix in Table 5. Results obtained are illustrated in Table 7.

With the normalized and weighted matrix, the next step is to estimate the distance that each alternative has from those referred to as ideal and anti-ideal. The results obtained from applying Equations (13) and (14) are illustrated in Table 8. These obtained distances generated decision indexes, illustrated in Table 9.

Table 7. Normalized and weighted values.

A^k	Attributes					
	IC	RP	NC	DI	SO	CS
A^1	0.1185	0.0293	0.0373	0.0436	0.0355	0.1778
A^2	0.0825	0.0275	0.0373	0.0433	0.0295	0.1509
A^3	0.0673	0.0293	0.0373	0.0391	0.0250	0.1096
A^4	0.1028	0.0366	0.0559	0.0577	0.0295	0.1282
A^5	0.0927	0.0348	0.0373	0.0385	0.0331	0.1716
A^6	0.1113	0.0403	0.0559	0.0577	0.0347	0.1757
A^+	0.0673	0.0403	0.0373	0.0385	0.0355	0.1778
A^-	0.1185	0.0275	0.0559	0.0577	0.0250	0.1096

Table 8. Distance to the ideal alternative and anti-ideal.

Alternative	Distance to Ideal Alternative						$\rho(A^k, A^+)$
	CI	MC	LDH	SO	MA	CS	
A^1	0.00262	0.00012	0.00000	0.00003	0.00000	0.00000	0.05256
A^2	0.00023	0.00016	0.00000	0.00002	0.00004	0.00072	0.03428
A^3	0.00000	0.00012	0.00000	0.00000	0.00011	0.00465	0.06990
A^4	0.00126	0.00001	0.00035	0.00037	0.00004	0.00246	0.06701
A^5	0.00064	0.00003	0.00000	0.00000	0.00001	0.00004	0.02678
A^6	0.00193	0.00000	0.00035	0.00037	0.00000	0.00000	0.05149
Alternative	Distance to Anti-Ideal Solution						$\rho(A^k, A^-)$
	CI	MC	LDH	SO	MA	CS	
A^1	0.00000	0.00000	0.00035	0.00020	0.00011	0.00465	0.07290
A^2	0.00680	0.00075	0.00139	0.00187	0.00087	0.02278	0.18563
A^3	0.00453	0.00086	0.00139	0.00153	0.00063	0.01201	0.14472
A^4	0.01058	0.00134	0.00313	0.00333	0.00087	0.01643	0.18887
A^5	0.00859	0.00121	0.00139	0.00148	0.00110	0.02944	0.20786
A^6	0.01238	0.00162	0.00313	0.00333	0.00120	0.03088	0.22922

Table 9. Decision indexes.

A^k	$\rho(A^k, A^+)$	$\rho(A^k, A^-)$	RC Index	Order
A^1	0.05256	0.07290	0.41892251	6
A^2	0.03428	0.18563	0.15587252	2
A^3	0.06990	0.14472	0.32567311	5
A^4	0.06701	0.18887	0.26187764	4
A^5	0.02678	0.20786	0.11411747	1
A^6	0.05149	0.22922	0.18343005	3

Attending to the distance from the ideal solution, the lowest distance is represented by A^5 , and that alternative must be selected; however, attending to distance from the anti-ideal solution, the biggest distance is represented by A^6 ; however, due to the weights in attributes, the best RC index is for A^5 , and this alternative must be the one selected.

4. Conclusions

This paper presents a hybrid technique that combines AHP and TOPSIS for the selection of agricultural technology, and a case study of tractor selection is presented as an example. However, the tractor evaluation here reported is for a group of farmers that have specific needs and preferences, and consequently, the result obtained is a response to their proper needs; and another group of farmers in another country, with other needs and working conditions, may have different levels of preference of attributes to those here reported; hence, the results can be different.

The hybrid technique is easy for users to use and understand, so it has been widely accepted, as it uses the similarity concept for evaluating a set of alternatives in relation to one ideal and another anti-ideal alternative. Thus, the AHP-TOPSIS technique has the following advantages over other multicriteria techniques:

- This hybrid technique does not require the use of specialized and expensive software for the evaluation of alternatives, as occurs with other techniques that, given their complexity, need to be integrated into specific computer applications.
- This hybrid technique can be applied using any spreadsheet, such as Excel, which is a component of Microsoft Office© and is present in most company computer equipment, therefore widely available to users. With the spreadsheet, the application is made just integrating the attributes weighting process with AHP, as well as the alternatives' comparison with TOPSIS.
- Given that the analysis can be performed with software widely integrated into desktops and laptops, most farmers or decision makers, people who know the selection problem, are able to evaluate tractors alternatives by themselves; this includes small, medium and large agribusinesses worldwide, since Microsoft Office is widely-used commercial software present in almost all systems.
- Therefore, as the selection and decision process is carried out by the company's staff, farmers avoid outsourcing this task and decision to experts in multicriteria techniques, who are usually unaware of the investment problem and farmers' needs.
- Furthermore, consequential costs incurred due to outsourcing external staff to perform the selection process are avoided.
- The AHP and TOPSIS techniques are very simple to understand and implement, so the time spent performing the evaluation is minimal, allowing managers and farmers to carry out other activities.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP: Analytic hierarchy process
 TOPSIS: Technique for order of preference by similarity to the ideal solution
 AT: Advanced technology
 ET: Economic techniques
 NPV: Net present value
 IRR: Internal rate of return
 PB: Pay back
 ST: Strategic techniques
 CEO: Chief Executive Officer
 LAM: Linear additive model
 ATA: Advanced technology in agriculture
 AMT: Advanced manufacturing technology
 SAGARPA: Ministry of Agriculture, Livestock, Rural Development, Fisheries and Food (in Mexico).
 SEDER: Ministry of Rural Development (in Mexico)
 CI: Consistency Index
 CR: Consistency ratio
 AI: Random Index
 OV: Objective values
 SV: Subjective values
 TSV: Total subjective values
 FDM: Final decision matrix
 IC: Initial cost of the tractor
 RP: Rated power
 NC: Number of cylinders
 DI: Displacement
 SO: Safety for operator
 CS: Customer service

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