

Article **Lean Manufacturing Assessment: Dimensional Analysis with Hesitant Fuzzy Linguistic Term Sets**

William Alexander Chitiva-Enciso [,](https://orcid.org/0000-0002-2656-6358) Luis Asunción Pérez-Domínguez * [,](https://orcid.org/0000-0003-2541-4595) Roberto Romero-López [,](https://orcid.org/0000-0003-0859-327X) David Luviano-Cruz [,](https://orcid.org/0000-0002-4778-8873) Iván Juan Carlos Pérez-Olguín and Luis Carlos Méndez-González

> Departamento de Ingeniería Industrial y Manufactura, Universidad Autónoma de Ciudad Juárez, Av. Plutarco Elías Calles 1210 Fovissste Chamizal, Ciudad Juárez 32310, Mexico; al228149@alumnos.uacj.mx (W.A.C.-E.); rromero@uacj.mx (R.R.-L.); david.luviano@uacj.mx (D.L.-C.); ivan.perez@uacj.mx (I.J.C.P.-O.); luis.mendez@uacj.mx (L.C.M.-G.) ***** Correspondence: luis.dominguez@uacj.mx

Abstract: Lean Manufacturing has become, in recent years, one of the most important philosophies for improving production and organizational systems. The literature shows that Hesitant Fuzzy Linguistic Terms Sets (HFLTSs) are highly capable of manipulating the uncertainty that the judgments made by evaluators carry and that they are subject to their perception, especially when used in combination with multicriteria decision making (MCDM) for the measurement of indicators in this type of system, as well as their general performance. However, it is still of interest to researchers to develop techniques and instruments that facilitate the measurement of the results obtained after applying this philosophy in organizations. This article proposes a model for the evaluation of the Lean Manufacturing performance through the Analytic Hierarchy Process (AHP) and Dimensional Analysis (DA) using HFLTSs. The results obtained show that the proposed model is a solid tool for the evaluation of Lean Manufacturing systems from a different perspective and that it can be integrated into the issuance of evaluations in a better way by considering human subjectivity. At the same time, it offers a strategy to create priorities in the action plans that Lean system managers propose after evaluating. However, it is important to apply the proposed model to multiple organizations and analyze the results obtained to maximize its benefits.

Keywords: MCDM; lean manufacturing; dimensional analysis; HFLTS; AHP

1. Introduction

Lean Manufacturing is a set of functional tools for reducing waste and increasing productivity in industries through the implementation of a culture of continuous improvement in production systems and organizational activities [\[1\]](#page-12-0). In this mode, those functional tools are immersed in a context of continuous improvement that implies establishing indicators that can be measured to implement improvement actions in organizations in such a way that multiple research studies have been carried out that address this topic [\[2,](#page-12-1)[3\]](#page-12-2). Lean Manufacturing is important for the improvement in production systems and requires continuous improvement to be effective [\[4\]](#page-12-3). The Lean approach is a way of organizing production and service that focuses on waste elimination. Waste is any activity that does not add value to the final product or service. By eliminating waste, the Lean approach can improve efficiency, productivity, revenue, and customer value [\[5\]](#page-12-4).

In another way, multicriteria decision making (MCDM) is a methodology that helps with decision making by comparing alternatives based on multiple criteria and preferences [\[6,](#page-12-5)[7\]](#page-12-6). Numeric values do not always reflect real human preferences, so they may be inadequate for decision making in complex situations [\[8\]](#page-12-7). Over the years, MCDM has become a topic of high interest to researchers, who have worked on these methods in order to solve problems from multiple dimensions and developed strategies that lead to the optimization of the prioritization of alternatives $[9,10]$ $[9,10]$. Likewise, the literature shows that the

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use of MCDM approaches in fuzzy environments, like the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [\[11,](#page-12-10)[12\]](#page-12-11), Analytic Network Process (ANP) [\[13\]](#page-12-12), Programmation Methodes Evaluating Expert Choices (PROMETHEE) [\[14\]](#page-12-13), Simple Additive Weighting (SAW) [\[15\]](#page-12-14), Elimination and Choice Translating Reality (ELECTRE) [\[16\]](#page-13-0) , Multicriteria Optimization and Compromise Solution (VIKOR) [\[17](#page-13-1)[,18\]](#page-13-2), Decision Making Trial and Evaluation Laboratory (DEMATEL) [\[19\]](#page-13-3), and Analytic Hierarchy Process (AHP) [\[20,](#page-13-4)[21\]](#page-13-5), applied to Lean Manufacturing can be an alternative for the management of this type of processes, but it can also be applied in aspects such as failure reduction, supplier selection, or the application of environmentally sustainable practices.

Thereby, Dimensional Analysis (DA) is a mathematical method that allows you to combine different attributes with different units of measurement into a single number. This is useful for problems where you need to compare or rank different options but the attributes you are considering are not directly comparable [\[22](#page-13-6)[,23\]](#page-13-7). However, DA is not as good at handling imprecise or subjective information, which is common in MCDM problems [\[24\]](#page-13-8). Rodriguez et al. [\[25\]](#page-13-9) propose the Hesitant Fuzzy Linguistic Terms Sets (HFLTSs) as an alternative that provides flexibility to decision makers, allowing for the use of linguistic variables to express their evaluations [\[26\]](#page-13-10), and at the same time, it is close to human language [\[27,](#page-13-11)[28\]](#page-13-12). In other words, terms such as "good", "bad", "excellent", or "poor" are assimilated more effectively into the human cognitive system and facilitate decision making when contrasting an indicator against multiple criteria [\[29,](#page-13-13)[30\]](#page-13-14).

Besides, the Key Performance Indicators (KPIs) allow for the performance of an organization or an area of it to be measured in quantitative terms in such a way that when evaluating them, it expresses the success obtained, and these have a guiding function for the creation of strategies but are also motivational for managers and work teams to achieve goals [\[31\]](#page-13-15). Published works such as [\[32\]](#page-13-16) propose the use of MCDM in new works for the prioritization of KPIs. The use of MCDM is viable for prioritizing KPIs, as evidenced in [\[33\]](#page-13-17), and evaluating performance in industrial systems, as shown in [\[34\]](#page-13-18). However, it is often difficult to assess Lean Manufacturing KPIs, set priorities to improve performance, and design an action plan, taking multiple criteria into consideration [\[12\]](#page-12-11).

The main contributions of this paper are:

- A novel hybrid model of Dimensional Analysis (DA) and Hesitant Fuzzy Linguistic Terms Sets (HFLTSs) for a Lean Manufacturing performance assessment as an alternative to prioritize continuous improvement and maximize productivity from a Fuzzy Linguistic Terms Sets perspective.
- To propose the use of HFLTSs to evaluate KPIs, managing the uncertainty of value judgments that arise from the evaluators' perceptions.
- To identify KPIs that are priorities for the design of action plans.
- To demonstrate the applicability of the proposed mathematical model for the evaluation of Lean Manufacturing systems.

The structure of this paper is as follows: The basic concepts are reviewed in Section [2.](#page-1-0) The problem and research methodology are illustrated in Section [3.](#page-3-0) The illustrative case is described in Section [4.](#page-4-0) The results and discussions are presented in Section [5.](#page-7-0) Finally, conclusions and avenues for future directions are drawn in Section [6.](#page-11-0)

2. Basic Concepts

This section addresses the basic concepts necessary for research on HFLTSs and DA.

2.1. Hesitant Fuzzy Linguistic Term Sets

Definition 1 ([\[25\]](#page-13-9)). Let *S* be a set of linguistic terms $S = \{S_0...S_g\}$ of an HFLTS; HS is a finite *ordered subset of the consecutive linguistic terms of S, where S is defined as the set of linguistic terms* $S = \{S_0, \ldots, S_g\}$ *to define the empty* HFLTS *and the complete* HFLTS *for a linguistic variable ϑ as follows:*

empty HFLTS: $HS(\theta) = 0$,

filled HFLTS: $HS(\theta) = S$.

In other words, a set of linguistic terms can be interpreted as a scale that groups together the evaluations that an evaluator can issue on a performance indicator. Lean system managers generally measure the performance of their systems through quantitative values. However, sets of linguistic terms represent an alternative to making judgments by using qualitative values that are more easily integrated into human psychology and that are associated with numerical values for mathematical manipulation. Definition 2 shows the set of linguistic terms proposed for our method.

Definition 2. Let *S* be a set of linguistic terms, $S = (S_1 : null, S_2 : insight$ insignificant, $S_3 : Almost$ *insigni f icant*, *S*⁴ : *Neutral*, *S*⁵ : *Good*, *S*⁶ : *Outstanding*, *S*⁷ : *Excellent*).

Definition 3 ([\[25\]](#page-13-9)). *The upper bound* H_S + *and lower bound* H_S *of the HFLTS* H_S *are defined as*

$$
H_{\{S+\}} = \max(s_i) = S_j, S_i \in H_S \text{ and } S_i \le S_j \forall i;
$$
 (1)

$$
H_{\{S-\}} = \min(s_i) = S_j, S_i \in H_S \text{ and } S_i \ge S_j \forall i.
$$
 (2)

Definition 4 ([\[25\]](#page-13-9))**.** *The envelope of the HFLTSs, env(HS), is a linguistic interval whose limits are obtained by means of an upper bound (max) and lower bound (min). Hence,*

$$
env(HS) = [HS-, HS+] \t\t(3)
$$

Definition 5 ([\[25\]](#page-13-9)). Let H_S^1 and H_S^2 be the two HFLTS and $env(H_S^1) = [s_p, s_q]$ and $env(H_S^2) = [s_{p'}, s_{q'}]$, then

$$
d(H_S^1, H_S^2) = |q' - q| + |p' - p| \tag{4}
$$

is called the distance between H_S^1 *and* H_S^2 *. Where*

- *d is the distance between* H_S^1 *and* H_S^2 *.*
- *p* and p' are the minimum value for H_S^1 and H_S^2 , respectively;
- *q* and *q'* are the maximum value for H_S^1 and H_S^2 , respectively.

2.2. Dimensional Analysis

Dimensional Analysis (DA) is an MCDM that generates an index of similarity that allows one to compare each alternative with an ideal solution, where the alternative closest to the ideal solution is the preferred one [\[24\]](#page-13-8).

Definition 6. Let R_i be the decision matrix of size mxn; the index of similarity IS_i will be obtained *from the Dimensional Analysis from*

$$
IS_i = \prod_{i=1}^{n} \left(\frac{D_{ij}}{A_i}\right)^{W_i} \text{ and } A_i \ge 1
$$
\n⁽⁵⁾

Applying logarithm properties, the above equation can be written as

$$
IS_i = \prod_{i=1}^{n} W_i * [\ln(D_{ij}) - \ln(A_i)] \text{ and } A_i \ge 1
$$
 (6)

where:

- *IS*^{*i*} is the similarity index of each KPI ^{*i*} to the ideal solution;
- W_i is the weight of the C_i with respect to all criteria, calculated by using AHP;
- D_{ij} is each ij value from the D matrix;
- A_i is the *i* value from vector A for each D_{ij} .

3. Method

Uncertain and imprecise data and information are typically present in MCDM problems. We present a distance between two HFLTSs that may be computed with the aid of HFLTS envelopes for the comprehensive design of steps for DA in HFLTSs. Figure [1](#page-3-1) shows the proposed method in general terms in order to facilitate its visualization.

Figure 1. Flowchart of the algorithm to evaluate Lean Manufacturing by using HFLTS and DA.

Therefore, the distance between two linguistic intervals can be calculated through the previous definition. After this, a method for measuring Lean Manufacturing is proposed, which is developed with the following steps:

Step 1. Determine $X^l = [H_{S_{ij}}]_{mxn}$ as a fuzzy evaluation matrix for the Lean Manufacturing assessment. The following notations are used to depict the considered problems:

 $E = e_1, e_2, \dots, e_k$ is the set of performance evaluators, and $A = C_1, C_2, \dots, C_n$ is the set of criteria used for evaluating the indicators.

The performance of alternative A_i with respect to a performance evaluator e_i and criterion *C^j* is denoted as *HSij* in a group decision environment with *K* persons.

Step 2. We calculate the one assessment matrix X by aggregating the perceptions of performance evaluators $(X^1, X^2, ..., X^K)$, where

$$
s_{p_{ij}} = \min\{\min_{l=1}^{K}(\max H_{S_{ij}}^l), \max_{l=1}^{K}(\min H_{S_{ij}}^l)\}\
$$
(7)

and

$$
s_{q_{ij}} = \max\{\min(\max H_{S_{ij}}^l), \max(\min H_{S_{ij}}^l)\}\tag{8}
$$

The performance of indicator KPI_i with respect to criterion C_j is denoted as x_{ij} in an aggregated matrix X.

Step 3. Establish the weighting of the evaluation criteria in the vector w_i by using the Analytical Hierarchical Process (AHP) according to the method proposed by [\[35\]](#page-13-19).

Step 4. Calculate the ideal solution vector *A* by using Equation [\(9\)](#page-3-2): Let be a collection of benefit criteria (i.e., the larger *C^j* , the greater the preference) and A be a collection of the cost criteria (i.e., the smaller *C^j* , the greater the preference). The HFLTS ideal solution denoted as $A = (A_1, A_2, ..., A_n)$ is defined as follows:

$$
A = [((\max_{l=1}^{K} (\max_{i} H_{S_{ij}}^{l}))|j \in \Omega_{b}, (\min_{l=1}^{K} (\min_{i} H_{S_{ij}}^{l}))|j \in \Omega_{c}), ((\max_{l=1}^{K} (\max_{i} H_{S_{ij}}^{l}))|j \in \Omega_{b}, (\min_{l=1}^{K} (\min_{i} H_{S_{ij}}^{l}))|j \in \Omega_{c})]
$$
(9)
\n $i = 1, 2, ..., m,$
\n
$$
A = (A_{1}, A_{2}, ..., A_{n})
$$

where $A_j = [a_{pj}, a_{qi}](j = 1, 2, ..., n)$.

Step 5. Construct an ideal separation matrix D, which is defined as follows:

$$
D = \begin{pmatrix} d(ln(x_{11}), ln(A_1)) & + & d(ln(x_{12}), ln(A_2)) & + & \cdots & + & d(ln(x_{1n}), ln(A_n)) \\ d(ln(x_{21}), ln(A_1)) & + & d(ln(x_{22}), ln(A_2)) & + & \cdots & + & d(ln(x_{2n}), ln(A_n)) \\ \vdots & & \vdots & & \vdots \\ d(ln(x_{m1}), ln(A_1)) & + & d(ln(x_{m2}), ln(A_2)) & + & \cdots & + & d(ln(x_{mn}), ln(A_n)) \end{pmatrix}
$$
(10)

Step 6. For each element *C^j* , the product with its respective *W^j* will be calculated in such a way that

$$
D_w = \begin{pmatrix} (D_{11}) * (w_1) & + & (D_{12}) * (w_2) & + & \cdots & + & (D_{1n}) * (w_j) \\ (D_{21}) * (w_1) & + & (D_{22}) * (w_2) & + & \cdots & + & (D_{2n}) * (w_j) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (D_{m1}) * (w_1) & + & (D_{m2}) * (w_2) & + & \cdots & + & (D_{mn}) * (w_j) \end{pmatrix} \tag{11}
$$

Step 7. Ranking the KPIs.

4. Illustrative Case

To illustrate the proposed model, the case proposed by [\[12\]](#page-12-11) for the assessment of the Lean Manufacturing performance was used as an experiment. This case presents a real-life example, which was applied in an automotive company based in Ciudad Juárez, Chihuahua, Mexico. The company uses an LM methodology and focuses on minimizing operational waste; thus, managers are particularly interested in assessing the real impact of the LM methodology. For this, a team of performance evaluators first assessed the company's LM implementation improvement metrics. Simultaneously, the case described the set of criteria and the KPIs depicted like alternatives as follows: *C*1: defects, *C*2: productivity, C_3 : lead time, C_4 : customer, C_5 : demand satisfaction, C_6 : cycle time, C_7 : tack time, *C*8: effectiveness, *C*9: levels of inventory, and *C*10: suppliers. Additionally, during the evaluation of Lean projects, nineteen alternatives to be considered are summarized: *KPI*1: sales, *KPI*2: market share, *KPI*3: maintenance, *KPI*4: OEE, *KPI*5: on-time delivery, *KPI*6: 5S, *KPI*7: kaizen, *KPI*8: bottleneck removal, *KPI*9: cross-functional work force, *KPI*10: focused factory production, *KPI*11: JIT/continuous flow production, *KPI*12: lot size reductions, *KPI*13: maintenance optimization, *KPI*14: process capability measurements, *KPI*15: kanban, *KPI*₁₆: quick changeover, *KPI*₁₇: total quality management, *KPI*₁₈: self-directed work teams, and *KPI*19: safety improvement programs.

Step 1. Determine the fuzzy evaluation matrix $X^l = [H_{S_{ij}}]$ for the MCDM problem. KPIs are evaluated with respect to each of the criteria. The performance evaluators *e*1,*e*2, and *e*³ establish the *X*¹ matrix in Table [1,](#page-4-1) while the performance evaluators *e*4,*e*5, and *e*⁶ establish the X_2 matrix in Table [2.](#page-5-0)

Table 1. *Cont.*

Table 2. *X*₂ Matrix.

	C_1	C ₂	C_3	C_4	C_5	C ₆	C_7	C_8	C ₉	C_{10}
KPI_1	$\{S_2, S_5\}$	${S_3, S_4}$	$\{S_2, S_7\}$	${S_4, S_5}$	${S_2, S_3}$	${S_5, S_6}$	$\{S_1, S_2, S_3\}$	$\{S_1\}$	${S_1, S_5}$	$\{S_1, S_2, S_3\}$
KPI ₂	$\{S_1, S_4\}$	$\{S_6, S_7\}$	$\{S_2, S_4\}$	$\{S_1, S_3, S_4\}$	$\{S_1, S_2\}$	$\{S_1, S_2\}$	$\{S_3, S_4\}$	$\{S_2, S_4, S_5\}$	$\{S_7\}$	$\{S_5, S_6\}$
KPI_3	$\{S_1, S_2\}$	$\{S_4, S_5\}$	$\{S_4, S_5\}$	$\{S_3, S_6\}$	$\{S_1, S_3\}$	$\{S_1, S_4\}$	$\{S_1\}$	$\{S_2, S_3, S_5\}$	$\{S_2, S_3, S_4\}$	$\{S_2, S_3\}$
KPI_4	$\{S_2, S_3, S_4\}$	$\{S_2, S_4\}$	$\{S_6,S_7\}$	$\{S_7\}$	$\{\dot{S}_5, S_6, \dot{S}_7\}$	$\{\vec{S}_1, \vec{S}_2, \vec{S}_4\}$	$\{S_1, S_2, S_7\}$	${S_1, S_4}$	$\{S_1, S_7\}$	$\{S_6, S_7\}$
KPI_5	$\{S_4, S_5\}$	$\{S_2, S_3\}$	$\{S_1\}$	$\{S_2, S_5, S_7\}$	$\{S_1, S_2, S_5\}$	$\{S_7\}$	$\{S_1, S_3\}$	$\{S_1, S_2, S_3\}$	$\{S_5, S_6\}$	$\{S_2, S_3\}$
KPI_6	$\{S_2, S_4\}$	$\{S_1, S_3\}$	$\{S_7\}$	${S_4, S_6}$	$\{S_2, S_4, S_5\}$	${S_1, S_6}$		$\{S_5, S_7\}$	$\{S_7\}$	$\{S_2, S_4, S_6\}$
KPI ₇	$\{S_3, S_4\}$	${S_4, S_7}$	$\{\dot{S}_5, \dot{S}_6\}$	$\{S_3, S_5, S_6\}$	${S_4, S_5}$	$\{\dot{S}_4, S_5, \dot{S}_7\}$	$\begin{Bmatrix} \{S_7\} \\ \{S_7\} \\ \{S_1\} \\ \{S_4, S_7\} \end{Bmatrix}$	$\{S_3, S_4\}$	$\{S_1, S_2, S_3\}$	${S_2, S_3}$
KPI_8	$\{S_1, S_2\}$	$\{S_5\}$	$\{S_4, S_7\}$	$\{S_6, S_7\}$	$\{S_7\}$	${S_1, S_2}$		$\{S_6, S_7\}$	$\{S_1, S_4\}$	$\{S_1, S_2, S_3\}$
KPI ₉	$\{S_7\}$	$\{S_1, S_2, S_5\}$	$\{S_5, S_6\}$	$\{S_5, S_6, S_7\}$	$\{S_5, S_6, S_7\}$	${S_2, S_3}$		$\{S_2, S_3, S_7\}$	$\{S_1, S_3\}$	${S_1, S_3}$
KPI_{10}	$\{S_3, S_4\}$	$\{S_7\}$	$\{S_3, S_4, S_5\}$	$\{S_1, S_2\}$	$\{S_5, S_6, S_7\}$	$\{S_6, S_7\}$	$\{S_2, S_4, S_5\}$	$\{S_6, S_7\}$	$\{S_2, S_3, S_7\}$	$\{S_5, S_7\}$
KPI_{11}	$\{S_1, S_2, S_3\}$	$\{S_2, S_4, S_6\}$	${S_4, S_6}$	$\{S_7\}$	$\{S_1, S_4, S_6\}$	$\{S_5, S_6\}$	$\{S_2, S_3, S_7\}$		$\{S_5, S_6, S_7\}$	$\{S_2, S_4, S_5\}$
KPI_{12}	${S_2, S_3}$	$\{S_5, S_6\}$	$\{S_1, S_5\}$	$\{S_6, S_7\}$	$\{S_1, S_2, S_5\}$	$\{S_7\}$	$\{S_1\}$	S_7 } {S ₇ }	$\{S_1, S_2, S_3\}$	$\{S_1\}$
KPI_{13}	$\{S_1, S_3\}$	${S_4, S_5}$	$\{S_3, S_4\}$	$\{S_1, S_2\}$	$\{S_5, S_6, S_7\}$	$\{S_1, S_3\}$	$\{S_6, S_7\}$	$\{S_1, S_3\}$	$\{S_1\}$	$\{S_7\}$
KPI_{14}	$\{S_4, S_5\}$	$\{S_2, S_3\}$ $\{S_7\}$	$\{S_2, S_3\}$	$\{S_2, S_3\}$	$\{S_1, S_2, S_3\}$	$\{S_1, S_2\}$	${S_4, S_5, S_6}$	${S_1, S_3}$	$\{S_1, S_2, S_5\}$	$\{S_5, S_6\}$
KPI_{15}	${S_4, S_5}$		$\{S_7\}$	$\{S_5, S_7\}$	$\{S_1, S_2, S_7\}$	$\{S_1, S_2\}$	${S_2, S_3}$	$\{S_7\}$	$\{S_5, S_7\}$	$\{S_1, S_2\}$
KPI_{16}	$\{S_7\}$	${S_6, S_7}$	${S_6, S_7}$	$\{S_1, S_3, S_4\}$	$\{S_1, S_2, S_4\}$	$\{S_1, S_2\}$	$\{S_1\}$	$\{S_1, S_3\}$	$\{S_6, S_7\}$	$\{S_4, S_7\}$
KPI_{17}	$\{S_7\}$	$\{S_1, S_2\}$	${S_1, S_2}$	$\{S_1, S_6\}$	$\{S_2, S_3, S_6\}$	$\{S_5, S_6, S_7\}$	$\{S_1, S_5\}$	$\{S_4, S_5\}$	$\{S_1, S_4, S_5\}$	$\{S_4, S_5\}$
KPI_{18}	$\{S_1, S_2\}$	$\{S_1, S_3, S_4\}$	$\{S_1, S_3, S_4\}$	$\{S_3, S_4\}$	$\{S_3, S_4, S_7\}$	$\{S_1, S_3\}$	$\{S_4, S_5, S_7\}$	$\{S_1, S_2, S_3\}$	$\{S_2, S_3, S_5\}$	$\{S_1\}$
KPI_{19}	$\{S_1, S_2\}$	$\{S_2, S_5\}$	$\{S_2, S_5\}$	$\{S_1\}$	$\{S_5, S_6, S_7\}$	$\{S_2, S_4, S_6\}$	${S_3, S_6}$	$\{S_2, S_3, S_4\}$	$\{S_2, S_3\}$	$\{S_1, S_2, S_4\}$

Step 2. We calculate the aggregated matrix *X ^l* by using Equations [\(7\)](#page-3-3) and [\(8\)](#page-3-4). For this, we take the matrix X_1 and X_2 . Table [3](#page-5-1) shows the obtained X^l matrix.

Table 3. *X ^l* aggregated matrix.

Step 3. Establish the ponderation for each one of the criteria called through vector ω_j for the performance evaluation by using an Analytic Hierarchy Process (AHP) method proposed by [\[35\]](#page-13-19). Appraise the criteria with respect to DM preferences. Table [4](#page-6-0) shows AHP matrix:

ω^j = (0.237, 0.243, 0.174, 0.104, 0.049, 0.072, 0.056, 0.024, 0.022, 0.019)

	C ₁	C ₂	C_3	C_4	C_5	C_6	C ₇	C_8	C ₉	C_{10}
C_1			\mathcal{L}	4	6	4	5	9	9	8
C ₂			3	5	7	4	3	5	8	6
C_3	1/2	1/3	1	3	5	6	6	4	3	5
C_4	1/4	1/5	1/3	1	$\overline{2}$	4	2	5	7	
C_5	1/6	1/7	1/5	1/2			2	3	\mathcal{P}	2
C_6	1/4	1/4	1/6	1/4	1		3	5	$\overline{4}$	7
C ₇	1/5	1/3	1/6	1/2	1/2	1/3	1	4	5	6
C_8	1/9	1/5	1/4	1/5	1/3	1/5	1/4			\mathcal{P}
C_9	1/9	1/8	1/3	1/7	1/4	1/4	1/5			
C_{10}	1/8	1/6	1/5	1/7	1/2	1/7	1/6	1/2		

Table 4. AHP matrix.

Step 4. Calculate the ideal solution vector *A* by using Equation [\(9\)](#page-3-2):

 $A=\big(\big\{S_1,S_2\big\},\big\{S_7,S_7\big\},\big\{S_1,S_2\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\},\big\{S_7,S_7\big\}\big\}$

Step 5. Construct the distance matrix D by using Equation [\(11\)](#page-4-2) as shown in Table [5.](#page-6-1) Next, sum the values obtained in the D matrix as shown in Table [6.](#page-6-2)

Table 5. D matrix. Distance between the logarithms of aggregate matrix *X ^l* and the vector A.

	C_1	C ₂	C_3	C_4	C_5	C_6	C_7	c_{s}	C ₉	C_{10}
KPI_1	$0.693 + 1.253$	$0.56 + 0.56$	$0 + 1.253$	$0.56 + 0.336$	$0.847 + 0.56$	$0.847 + 0.336$	$0.847 + 0.56$	$1.946 + 0.154$	$0.336 + 0$	$0.847 + 0.847$
KPI ₂	$0 + 0.916$	$0.847 + 0.336$	$0.693 + 1.099$	$0.56 + 0.56$	$1.253 + 1.253$	$1.253 + 1.253$	$1.253 + 0.847$	$0.336 + 0.336$	$0.154 + 0$	$0.056 + 0.336$
KPI ₃	$0 + 1.099$	$0.56 + 0.56$	1.386 + 1.256	$0.847 + 0.847$	$0.847 + 0.336$	$0.56 + 0.56$	$1.943 + 0.56$	$0.336 + 0$	$0.56 + 0.154$	$1.946 + 1.253$
KPI ₄	$0.693 + 1.253$	$0.56 + 0.336$	$0 + 1.253$	$0.56 + 0$	$0.847 + 0.336$	$0.56 + 0.336$	$0.56 + 0$	$0.56 + 0.56$	$0.154 + 0$	$0.56 + 0.154$
KPI ₅	$0 + 0.916$	$0.847 + 0.336$	$0 + 1.099$	$1.253 + 1.253$	$0.56 + 0.336$	$0.154 + 0$	$0.847 + 0.336$	$0.847 + 0.56$	$0.847 + 0.336$	$0.847 + 0.336$
KPI ₆	$0.693 + 1.099$	$0.847 + 0.56$	$0 + 1.253$	$0.847 + 0.56$	$0.336 + 0.154$	$1.253 + 0.847$	$0 + 0$	$0.154 + 0$	$0.336 + 0$	$0.154 + 0.154$
KPI ₇	$0 + 0.693$	$1.253 + 0.56$	$0.693 + 1.099$	$1.253 + 0.847$	$0.56 + 0.56$	$0.56 + 0.56$	$0.154 + 0$	$0.56 + 0.336$	$0.847 + 0.56$	$0.847 + 0.154$
KPI_8	$0 + 1.253$	$0.336 + 0.336$	$0 + 1.253$	$0.154 + 0$	$0.847 + 0$	$1.253 + 0.847$	$1.946 + 1.253$	$0.847 + 0.154$	$0.56 + 0.56$	$0.847 + 0.847$
KPI ₉	$1.386 + 1.253$	$0.336 + 0.154$	$1.609 + 1.253$	$0.56 + 0.336$	$0.56 + 0.336$	$0.847 + 0.336$	$0.847 + 0.56$	$1.253 + 0.56$	$0.847 + 0.336$	$0.847 + 0.847$
KPI_{10}	$1.099 + 1.253$	$0 + 0$	$0 + 1.253$	$1.253 + 0.847$	$1.253 + 0.336$	$0.154 + 0.154$	$1.253 + 0.336$	$0.154 + 0.154$	$0.336 + 0$	$1.946 + 0.336$
KPI_{11}	$0 + 1.253$	$1.253 + 0.847$	$0 + 1.099$	$0.154 + 0$	$0.154 + 0.154$	$0.56 + 0.336$	$0.56 + 0$	$0.154 + 0$	$0.336 + 0$	$0.336 + 0.154$
KPI_{12}	$0.693 + 1.253$	$0.336 + 0.336$	$0 + 1.253$	$0.336 + 0.154$	$0.336 + 0.154$	$0.154 + 0$	$1.946 + 1.946$	$0.154 + 0$	$0.847 + 0.336$	$1.946 + 1.253$
KPI_{13}	$0 + 1.253$	$0.336 + 0.336$	$1.099 + 0.916$	$1.253 + 0.56$	$0.56 + 0.336$	$0.847 + 0.847$	$0.154 + 0$	$1.946 + 0.847$	$1.946 + 0.56$	$0.154 + 0$
KPI ₁₄	$0.693 + 0.916$	$0.847 + 0.336$	$0.693 + 1.099$	$0.847 + 0$	$0.847 + 0.56$	$1.253 + 0.336$	$0.56 + 0.154$	$0.847 + 0.336$	$0.336 + 0.336$	$0.56 + 0.336$
KPI_{15}	$1.386 + 1.099$	$0 + 0$	$0 + 1.253$	$0.336 + 0.336$	$1.946 + 1.253$	$1.253 + 1.253$	$1.253 + 1.253$	$0.154 + 0$	$0.847 + 0.336$	$1.253 + 0.847$
KPI_{16}	$0 + 1.253$	$0.154 + 0.154$	$0 + 1.253$	$0.56 + 0.154$	$0.56 + 0.56$	$1.253 + 0.56$	$1.946 + 1.253$	$0.847 + 0$	$1.946 + 0.154$	$0.56 + 0.56$
KPI_{17}	$1.099 + 1.253$	$1.946 + 1.253$	$0 + 1.253$	$0.336 + 0.154$	$1.253 + 1.253$	$0.56 + 0.336$	$0.336 + 0.154$	$0.56 + 0.56$	$1.946 + 0.336$	$0.847 + 0.56$
KPI_{18}	$0 + 1.099$	$1.253 + 0.56$	$0 + 1.253$	$0.56 + 0.56$	$1.253 + 0.847$	$0.847 + 0$	$0.56 + 0.56$	$0.847 + 0.154$	$1.946 + 1.253$	$1.946 + 1.946$
KPI_{19}	$0 + 1.253$	$1.253 + 1.253$	$0.693 + 1.253$	$1.946 + 1.253$	$1.253 + 0.336$	$1.946 + 1.253$	$1.253 + 0.847$	$0.56 + 0.336$	$1.253 + 0.847$	$0.56 + 0.154$

Table 6. Sum of the values obtained in D matrix.

Step 6. The matrix obtained in the previous step is taken and each value is multiplied with the respective W_j . Table [7](#page-7-1) depicts the product between the matrix obtained in step 6 and the vector *W^j* .

	C ₁	C ₂	C_3	C_4	C_5	C_6	C_7	C_8	C_{9}	C_{10}
KPI_1	0.461	0.272	0.218	0.093	0.069	0.085	0.079	0.05	0.007	0.032
KPI ₂	0.217	0.288	0.312	0.116	0.123	0.18	0.118	0.016	0.003	0.017
KPI ₃	0.26	0.272	0.459	0.176	0.058	0.081	0.14	0.008	0.016	0.061
KPI ₄	0.461	0.218	0.218	0.058	0.058	0.065	0.031	0.027	0.003	0.014
KPI_5	0.217	0.288	0.191	0.261	0.044	0.011	0.066	0.034	0.026	0.022
KPI_6	0.425	0.342	0.218	0.146	0.024	0.151	Ω	0.004	0.007	0.006
KPI ₇	0.164	0.44	0.312	0.218	0.055	0.081	0.009	0.022	0.031	0.019
KPI_8	0.297	0.164	0.218	0.016	0.042	0.151	0.179	0.024	0.025	0.032
KPI_{9}	0.625	0.119	0.498	0.093	0.044	0.085	0.079	0.043	0.026	0.032
KPI_{10}	0.557	Ω	0.218	0.218	0.078	0.022	0.089	0.007	0.007	0.043
KPI_{11}	0.297	0.51	0.191	0.016	0.015	0.065	0.031	0.004	0.007	0.009
KPI_{12}	0.461	0.164	0.218	0.051	0.024	0.011	0.218	0.004	0.026	0.061
KPI_{13}	0.297	0.164	0.351	0.188	0.044	0.122	0.009	0.067	0.055	0.003
KPI_{14}	0.381	0.288	0.312	0.088	0.069	0.114	0.04	0.028	0.015	0.017
KPI_{15}	0.589	0	0.218	0.07	0.157	0.18	0.14	0.004	0.026	0.04
KPI_{16}	0.297	0.075	0.218	0.074	0.055	0.13	0.179	0.02	0.046	0.021
KPI_{17}	0.557	0.777	0.218	0.051	0.123	0.065	0.027	0.027	0.05	0.027
KPI_{18}	0.26	0.44	0.218	0.116	0.103	0.061	0.063	0.024	0.07	0.074
KPI_{19}	0.297	0.609	0.339	0.333	0.078	0.23	0.118	0.022	0.046	0.014

Table 7. *D^w* matrix. Product between the matrix obtained in step 6 and the vector *W^j* .

Step 7. The final ranking is calculated from the product of the values obtained by each row i in the previous matrix. In this sense, Table [8](#page-7-2) shows the final ranking calculated.

Table 8. Final ranking.

L.

5. Results Analysis and Discussion

The results of the final ranking show that *KPI*19, *KPI*18, and *KPI*¹⁷ are at a better level than the others, while it quickly allows KPI_6 , KPI_{10} , and KPI_{15} to be established at a priority level.

The ranking obtained in the case study was compared with that obtained by [\[12\]](#page-12-11). The basic statistics in Table [9](#page-7-3) were calculated by using statistical software. The mean and standard deviation have differences as a consequence of the Dimensional Analysis model assigning three KPIs in the last position as a tie.

Table 9. Overall statistics between rankings.

Table [10](#page-8-0) shows the comparison between the ranking obtained by [\[12\]](#page-12-11) and the ranking obtained with the proposed method. Notable differences are evident in most of the KPIs, with the exception of *KPI*7, *KPI*12, *KPI*13, and *KPI*15. The variation in the results could be explained by the variation in the set of linguistic terms used for each evaluation. However, repetition of the two methods in other Lean systems would be necessary to analyze the pattern of behavior in the results.

Table 10. Comparison between the ranking obtained by using the proposed method and the ranking obtained by [\[12\]](#page-12-11).

KPI_i	DA Ranking	TOPSIS Ranking
KPI_1	6	14
KPI ₂	9	$\overline{4}$
KPI_3	5	9
KPI_4	15	$10\,$
KPI_5	12	$\ensuremath{\mathfrak{Z}}$
KPI_6	17	$\,$ 8 $\,$
KPI ₇	11	11
KPI_8	10	5
KPI ₉	$\overline{4}$	16
KPI_{10}	17	6
KPI_{11}	$16\,$	$\mathbf{1}$
KPI_{12}	14	12
KPI_{13}	13	13
KPI_{14}	$\,8\,$	$\overline{2}$
KPI_{15}	17	19
KPI_{16}	7	$18\,$
KPI_{17}	\mathfrak{Z}	15
KPI_{18}	$\overline{2}$	7
KPI_{19}	$\mathbf{1}$	17

Table [11](#page-8-1) depicts the covariance matrix showing different variance values for each method, as well as the negative covariance that allows us to presume an inverse relationship between the rankings obtained through each methodology.

Table 11. Covariance matrix.

In addition to the similarity index obtained in the illustrative case, 15 more iterations were carried out as part of a sensibility analysis, and the results are depicted in Tables [12](#page-9-0) and [13.](#page-9-1)

	IT_0	IT_1	IT ₂	IT_3	IT_4	IT_5	IT_6	IT_7
KPI_{11}	$3.62E - 15$	1.74E-14	5.75E-14	1.07E-13	$1.23E-13$	7.35E-14	1.50E-13	6.37E-14
KPI_{12}	2.86E-13	1.37E-12	4.54E-12	8.43E-12	9.70E-12	5.80E-12	1.18E-11	$5.02F-12$
KPI_{13}	1.61E-12	7.72F-12	2.55E-11	4.74E-11	5.46E-11	$3.26E - 11$	$6.66E-11$	2.82E-11
KPI_{14}	6.81E-12	3.27E-11	$1.08E-10$	$2.01E-10$	$2.31E-10$	1.38E-10	$2.82E - 10$	1.20E-10
KPI_{15}	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$	$0.00E + 00$
KPI_{16}	$9.22F-12$	4.43E-11	$1.46E-10$	$2.72E-10$	$3.13E-10$	1.87E-10	$3.82E-10$	$1.62F-10$
KPI_{17}	3.78E-11	$1.82E-10$	$6.01E-10$	1.12E-09	1.28E-09	7.67E-10	1.57E-09	$6.65E-10$
KPI_{18}	$1.43E-10$	6.88E-10	2.27E-09	4.23E-09	4.86E-09	2.91E-09	5.93E-09	2.52E-09
KPI_{19}	5.79E-10	2.78E-09	9.19E-09	1.71E-08	1.97E-08	1.17E-08	2.40E-08	1.02E-08

Table 12. *Cont.*

Table 13. Sensibility analysis (B).

The line graph in Figure [2](#page-9-2) shows that the iterations, including the initial solution, have similar behavior even though the weight vector changed. All the iterations carried out yield the same ranking for the evaluated KPIs.

Figure 2. Linear behavior of calculated iterations.

The weighting vector was randomly changed to compare the results obtained. An analysis of variance was applied between the 16 calculated iterations. The *p*-value indicates that the variation in the similarity indices obtained can not be explained. The analysis of variance is shown in Table [14.](#page-10-0)

Table 14. Variance analysis.

Table [15](#page-10-1) shows the results of Tukey's pairwise comparison. This analysis allows us to affirm that there are no significant differences between the means of the iterations.

Factor	N	Average	Agrupation
IT_6	19	0.000000	A
IT_4	19	0.000000	A
IT11	19	0.000000	A
IT ₃	19	0.000000	А
IT_{13}	19	0.000000	A
IT_{15}	19	0.000000	А
IT_{12}	19	0.000000	A
IT_5	19	0.000000	А
IT_{14}	19	0.000000	A
IT_{10}	19	0.000000	A
IT ₉	19	0.000000	A
IT ₇	19	0.000000	A
IT ₂	19	0.000000	А
IT_8	19	0.000000	A
IT_1	19	0.000000	А
IT_0	19	0.000000	А

Table 15. Tukey's pairwise comparison.

Fisher's pairwise comparisons allow us to affirm that there are no significant differences between the means of the calculated iterations. Table [16](#page-10-2) shows Fisher's pairwise comparison.

Table 16. Fisher's pairwise comparison.

Factor	N	Average	Agrupation
IT_6	19	0.000000	A
IT_4	19	0.000000	A
IT_{11}	19	0.000000	A
IT ₃	19	0.000000	A
IT_{13}	19	0.000000	A
IT_{15}	19	0.000000	А
IT_{12}	19	0.000000	A
IT_5	19	0.000000	А
IT_{14}	19	0.000000	A
IT_{10}	19	0.000000	A
IT ₉	19	0.000000	A
IT ₇	19	0.000000	A
IT ₂	19	0.000000	A
IT_8	19	0.000000	A
IT_1	19	0.000000	A
IT_0	19	0.000000	А

Dunnett's multiple comparisons were performed by using the initial solution (IT_0) as control data. The results show that there are no significant differences between the means. This analysis is shown in Table [17.](#page-11-1)

Factor	N	Average	Agrupation
IT_0 (control)	19	0.000000	A
IT_6	19	0.000000	A
IT_4	19	0.000000	A
IT_{11}	19	0.000000	A
IT ₃	19	0.000000	A
IT_{13}	19	0.000000	A
IT_{15}	19	0.000000	A
IT_{12}	19	0.000000	А
IT_5	19	0.000000	A
IT_{14}	19	0.000000	A
IT_{10}	19	0.000000	A
IT ₉	19	0.000000	A
IT ₇	19	0.000000	А
IT ₂	19	0.000000	A
IT_8	19	0.000000	A
IT_1	19	0.000000	А

Table 17. Dunnett's multiple comparisons with a control.

6. Conclusions

The measurement of Lean Manufacturing performance indicators is a challenge faced by both experts and managers who must make decisions about their organizations. The presented method in this research constitutes a novel alternative to evaluate Lean Manufacturing systems by using a human perspective with a mathematical method such as DA to easily identify the KPIs that require action plans to guarantee the continuous improvement sought by the implemented Lean strategies. In summary, first of all, this method compares the criteria with each other. Second, group the diffuse perceptions that arise when evaluating each of these. And finally, the mathematical structure of the proposed method allows us to easily identify the indicators that require priority action plans for improvement.

The creation of action plans that meet the needs of implemented Lean systems continues to be a challenge that organizations must assume as part of the continuous improvement processes. The proposed method facilitates the identification of KPIs that should be considered a high priority for Lean system managers, who face the challenges of continuously improving their organizations.

It is expected that, by applying the proposed methodology, organizations will find a path that facilitates cost minimization and profit maximization. MCDM is a research topic that has gained importance in the management of production systems, and this hybridization could represent an alternative to the classical quantitative approach for the Lean Systems assessment. As part of future work, it is planned to develop software to implement the tool systematically in organizations. Likewise, it is contemplated to use neural networks and optimization algorithms to make simultaneous comparisons.

Given the contributions stated in the introduction, it is possible to affirm that:

- A novel model has been proposed that combines the mathematical technique of Dimensional Analysis with HFLTS to evaluate Lean Manufacturing.
- This method avoids directly evaluating KPIs with quantitative values and makes use of linguistic terms adjusted to human psychology, facilitating the making of judgments.
- The results of the illustrative case show that the mathematical structure of the model leads to easily identifying the KPIs that deviate from the ideal solution and require prioritization in continuous improvement plans.

It is feasible to apply the proposed method to manufacturing companies. However, the results could be compared with those obtained with other similar methods to study the behavior of the rankings obtained.

Future works could aim to implement the strategy presented in other problems, such as the choice of suppliers or human resources, among others. Also, they could consider the use of techniques such as neural networks, machine learning, and other metaheuristic models that expand the possibilities and maximize the benefits of the proposed model.

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