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Research Article

Expert System for Competences Evaluation 360° Feedback Using Fuzzy Logic

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Performance evaluation (PE) is a process that estimates the employee overall performance during a given period, and it is a common function carried out inside modern companies. PE is important because it is an instrument that encourages employees, organizational areas, and the whole company to have an appropriate behavior and continuous improvement. In addition, PE is useful in decision making about personnel allocation, productivity bonuses, incentives, promotions, disciplinary measures, and dismissals. There are many performance evaluation methods; however, none is universal and common to all companies. This paper proposes an expert performance evaluation system based on a fuzzy logic model, with competences 360° feedback oriented to human behavior. This model uses linguistic labels and adjustable numerical values to represent ambiguous concepts, such as imprecision and subjectivity. The model was validated in the administrative department of a real Mexican manufacturing company, where final results and conclusions show the fuzzy logic method advantages in comparison with traditional 360° performance evaluation methodologies.

1. Introduction

Nowadays, labor competences and competence evaluation represent a real challenge for organizations, which emerged in order to assign the right man to the right job. This evaluation method is based on questionnaires that involve fixed scales with specific values, such as 100%, 75%, 50%, 25%, and 0%. This kind of evaluation reduces the evaluator opportunity to express points of view and causes a rigid evaluation. Fuzzy set theory appears as an important tool to include inaccurate judgments inherent in personnel evaluation process. According to Butkiewicz [1] Fuzzy Logic is a very good tool for decision problems, especially when nonprecise or partially precise description is available. Although it can be applied with success in management problems, fuzzy logic is not common in this area.

Fuzzy Logic is an artificial intelligence (AI) technique [2]. AI comes with the purpose of developing models and programs of the intelligent behavior. One of the approaches of the AI is Logic, with the main objective of formalization of natural reasoning.

Fuzzy logic has two main components: membership functions and fuzzy rules. Using them it is possible to move a qualitative to a quantitative description, for example, to represent linguistic expressions as mathematic expressions. This is very useful when it is necessary to model the expertise of a human expert.

Fuzzy membership functions express the certainty than an element of the universe belongs to a fuzzy set. It represents the degree of truth as an extension of the valuation. Degrees of truth are very often confused with probabilities but they are conceptually different because fuzzy truth represents membership in vaguely defined sets, and not likelihood of an event. These membership functions can take different shapes according to expertise and preferences of the designer.

In these membership functions the x-axis represents the universe of discourse, and the y-axis represents the degrees of membership in the $[0, 1]$ interval. Most commonly used functions are triangular, trapezoidal, Gaussian, singleton, Gamma, and so forth. Membership functions can be expressed as a discrete or continuous function. In other words, $\mu_A(X)$ is a membership function of a set A, according to the elements of the universe.

Fuzzy sets are classes of objects with grades of membership. Each set is characterized by a membership function, which assigns a grade of membership to each object based on a characteristic.

When the universe of discourse is continuous and finite, commonly used notation to represent set A is

$$A = \int_x \frac{\mu_{A(x)}}{x}, \tag{1}$$

where

$$0 \le \mu_A(x) \le 1. \tag{2}$$

When the universe of discourse is discrete and finite, fuzzy set A is commonly represented as

$$A = \sum_{i=1}^{n} \frac{\mu_A(x_i)}{x_i} = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n}. \tag{3}$$

For instance, if fuzzy set A contains the elements x_1, x_2, x_3, x_4, and x_5 with membership degrees of 0, 0.5, 1, 0.5, and 0, respectively, the fuzzy set is expressed as

$$A = \frac{0}{x_1} + \frac{0.5}{x_2} + \frac{1}{x_3} + \frac{0.5}{x_4} + \frac{0}{x_5}. \tag{4}$$

A fuzzy set in a discrete and finite universe of discourse can be represented too as a set of ordered pairs of x and its membership degree in A as

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \tag{5}$$

which results in

$$A = \{(x_1, 0), (x_2, 0.5), (x_3, 1), (x_4, 0.5), (x_5, 0)\}. \tag{6}$$

Geometry of fuzzy sets involves three elements: domain, range, and mapping. In this example, geometry of the fuzzy set A is

domain: $\{x_1, x_2, x_3, x_4, x_5\}$,

range: $[0, 1]$,

mapping: $\mu A(x) \rightarrow [0, 1]; \{0, 0.5, 1, 0.5, 0\}$.

Graphically, fuzzy set A can be expressed as shown in Figure 1.

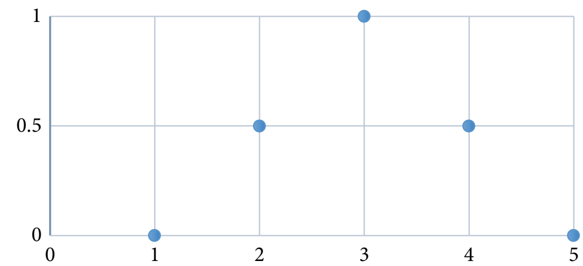

Figure 1: Graphical representation of a fuzzy set.

As in classic logic, fuzzy logic uses three basic operations in fuzzy sets: union, intersection, and complement. However, fuzzy sets have certain characteristics that make them different from classic sets. Fuzzy sets have elements with variable membership degrees, which means that an element of the universe of discourse can belong to one or more fuzzy sets, with different membership degrees.

The first operation on fuzzy sets is *intersection*. It is the degree of membership that two fuzzy sets share, that is, is the smallest degree of membership of each element in the fuzzy sets. Intersection of two fuzzy sets A and B is a fuzzy set $A \cap B$ in the universe of discourse X, whose function is given by

$$\mu_{A\cap B}(x) = \min[\mu_A(x), \mu_B(x)] = \underset{x}{\wedge}[\mu_A(x), \mu_B(x)], \tag{7}$$

where

$A \cap B$ represents the intersection of the fuzzy sets A and B;

$\wedge$ represents the minimum operator.

The operation *union* results as the biggest degree of membership of each element in the fuzzy sets, that is, the highest value of the fuzzy values. Union of two fuzzy sets A and B is a fuzzy set $A \cup B$ in the universe of discourse X, whose function is given by

$$\mu_{A\cup B}(x) = \max[\mu_A(x), \mu_B(x)] = \underset{x}{\vee}[\mu_A(x), \mu_B(x)], \tag{8}$$

where

$A \cup B$ represents the intersection of the fuzzy sets A and B;

$\vee$ represents the maximum operator.

The logic operation *complement* results as the degree of membership that the fuzzy set needs to reach the unit. The complementary set A of a fuzzy set A is that whose function is given by

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x). \tag{9}$$

Functions that define operations of intersection and union can be generalized using the triangular norm (called T-norm) and the triangular conorm (called T-conorm or S-norm), respectively.

A *t-norm operator* is a function of two elements $T(\cdot,\cdot)$ that satisfies the following.

Boundary Conditions. This condition implies the generalization of the classic sets:

$$T(a,0)=0,\\ T(a,1)=a. \tag{10}$$

Monotonicity. This condition implies that a decrease in the degree of membership for the set A or B will not produce an increase in the degree of membership of the intersection of the sets A and B:

$$T(a,b)\le T(c,d) \quad \text{if } a\le c,\ b\le d. \tag{11}$$

Commutative Property. This property indicates that the operator is indifferent to the order of the fuzzy sets that are combined:

$$T(a,b)=T(b,a). \tag{12}$$

Associative Property. This property allows calculating the intersection of any number of fuzzy sets, grouped in pairs, regardless of the order of couples:

$$T(a,T(b,c))=T(T(a,b),c). \tag{13}$$

In the same way, operator T-conorm (S-norm) is a function of two elements $S(\cdot,\cdot)$ that satisfies the following.

Boundary Conditions

$$S(a,1)=1,\\ S(a,0)=a. \tag{14}$$

Monotonicity

$$S(a,b)\le S(c,d) \quad \text{if } a\le c,\ b\le d. \tag{15}$$

Commutative

$$S(a,b)=S(b,a). \tag{16}$$

Associative

$$S(a,S(b,c))=S(S(a,b),c). \tag{17}$$

Some interesting contributions of fuzzy logic as a technique to model subjective viewpoints are found in [3], where the authors firstly considered decision making problems using fuzzy logic. Probably, the first attempt to apply fuzzy logic to personnel evaluation was proposed in [4, 5]. Another approach can be found in [6]. Cannavacciuolo et al. [4] presented the application of fuzzy set theory to a personnel evaluation procedure. Effectiveness of fuzzy concepts and methods depends on the approach used for the analysis of organizational issues. Fuzzy set theory allows them to model the weak signals existing in evaluation processes and highlights part of the tacit knowledge involved in individual judgments. Usually, researchers, consultants, and managers use a rather qualitative approach to organizational problems. However the natural language is the preferred instrument to describe the organizational conditions because the shades of meaning and the ambiguity of verbal statements allow the company actors to manage diverging opinions, tensions, and conflicts.

These approaches are detailed in [7–11].

On the other hand, the logical-mathematical models tend to represent a world of certainty and coherence where doubts, contradictions, divergences, polysemy, conflicts, and ambiguities are usually typified, dissolved, degraded, and linearized. Within this same conceptual framework, mathematicians, computer scientists, A.I. researchers, and engineers, in search of formal coherence, quantifiable variables, and efficient algorithms, usually tend to use fuzzy set theory without considering complexity and ambiguity in organizational situations, for example, [3, 12–18].

There seems to be a growing trend towards the use of systematic procedures in personnel selection. For instance, Karsak [19] introduced a method that integrates decision makers linguistic assessments about subjective factors such as excellence in oral communication skills, personality, leadership, and quantitative factors such as aptitude test score within multiple objective programming frameworks. The importance level of each goal is considered by applying the composition operator to the membership function of the goal and the membership function corresponding to its fuzzy priority defined by linguistic variables.

Kolarik et al. [20] present an online approach to monitoring human performance in terms of conditional reliability when a task is performed. Unlike traditional human reliability analysis, this approach develops a dynamic model that can cope with constantly changing conditions that affect operator performance. A fuzzy knowledge-based assessment approach is developed in order to deal with uncertainty and subjectivity associated with human performance assessment.

Podofellini et al. [21] assess the influence of the failure of the operators to perform one task on the failure probabilities of subsequent tasks with an approach called technique for human error rate prediction (THERP) and a fuzzy expert system (FES).

Other works include the use of fuzzy logic to evolve an optimal and accurate judgment according to the human thinking model and also to mitigate the commonly occurred biases in human recruitment and selection procedures, as seen in [22].

García et al. [23] propose, through the use of tools based on fuzzy logic, the evaluation of the impact of training in companies, by applying the reasoning characteristic of fuzzy logic, with the aim of complementing and extending the classical logic.

Tosti and Addison [24] refer that a poorly designed 360° feedback system can do more harm than good. The use of commercial 360° software is not always an option due to specific requirements of each organization. In this way, it may be that people who design 360° programs are well versed in assessment and measurement technology and woefully lacking in their understanding of feedback technology. Reliability of the 360 degree feedback is supported by the number and hierarchy of raters, as referred to in [25], assuming that personal qualities are developmental goals. Therefore, software has been designed specifically for this study evaluation.

This paper is organized as follows. Section 1 presents an introduction to the study. Section 2 shows some fundamental concepts about competences, performance evaluation 360° feedback, and competence evaluation methodology; fuzzy logic basis and a proposed fuzzy logic model are shown too. After that, the application of both systems (traditional 360° feedback system and fuzzy logic 360° feedback expert system) at the administrative area of a real manufacturing company in the state of Veracruz, Mexico, is shown. Section 3 shows clear and concise results while discussion about the significance of the results is developed. Finally, Section 4 describes the main conclusions of the study.

2. Expert System for Competences Evaluation 360° Feedback Using Fuzzy Logic

2.1. Competences. Personnel appraisal is considered as performance evaluation, and it is based on formal evaluation programs with reasonable information amount about employees and their job performance.

The literature describes several evaluation methods, each with its own advantages and drawbacks, and there is no ideal or universal method for all people, positions, organizations, and situations. The choice will depend on many other aspects such as

(i) position,

(ii) characteristics to be measured,

(iii) organizational culture,

(iv) objectives, achieved or to be achieved,

(v) circumstantial elements.

Performance evaluation methods are classified according to the feature they measure characteristics, behaviors, or outcomes, as referred to in [1]. Behavior methods enable the evaluator to identify how far the employee performance is away from a specific scale. These methods describe what actions should be exhibited during the position performance. It is mainly used to provide development-oriented feedback. According to Gomez-Mejia et al. [26], the main advantage in the performance measure adopting a behavior-based approach is that criteria or performance standards are concrete. Behavior scales give employees specific behavior examples that can make them successful (or avoid their success) in their work. If an employee knew the required skills for the position and the corresponding aperture in degrees, it could verify, analyze, and control its own behavior according to the requirements.

A competence is an underlying characteristic in the employee related to an effectiveness standard and superior performance in a job or situation, as discussed in [27].

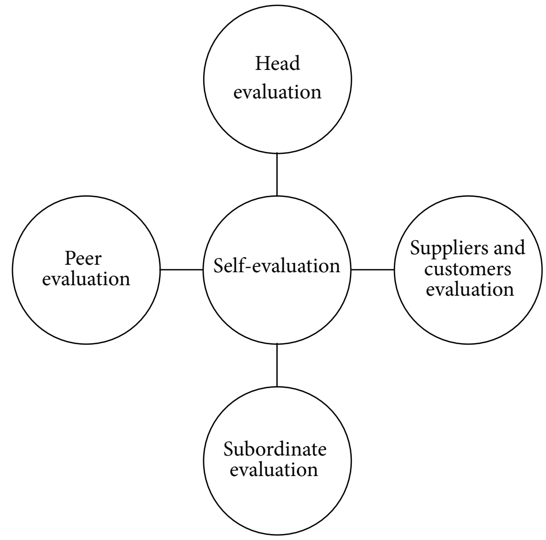

Figure 2: 360° evaluation scheme.

According to Levy-Leboyer [28], individual skills and company competences are closely related. Company competences are constituted by the integration and coordination of individual skills; however, these competences require an integration and coordination of knowledge and personal qualities. Individual competences are an individual property. Company competences are developed by individuals, but they belong to the company.

2.2. 360° Performance Evaluation. 360° performance evaluation is a sophisticated scheme that allows the employee to be evaluated by its surrounding bosses, peers, and subordinates (see Figure 2). A scheme may include suppliers or customers.

360° performance evaluation can potentially bring a globalized diagnosis about the employee performance, allowing the evaluator to compare different opinions about the level of competence expected in the evaluated person and then to take decisions about how to increase the level of compliance of this competences.

Alles [29] proposes 7 points for 360° evaluation.

(1) Identify cardinal and individual competences. If the company has implemented a performance evaluation system, the competences will be the same. Eventually, it is possible to use a reduced number of competences when using the 360° evaluation system.

(2) Design the tool. Questionnaires typically constitute the process support (see Figure 3).

(3) Select evaluators: superiors, partners, internal customers in other areas, customers, and external suppliers. Customers can be included or not. It is important to emphasize the fact that assessments are anonymous and that evaluators are chosen by the evaluating person.

(4) Launch the evaluation process with stakeholders and evaluators.

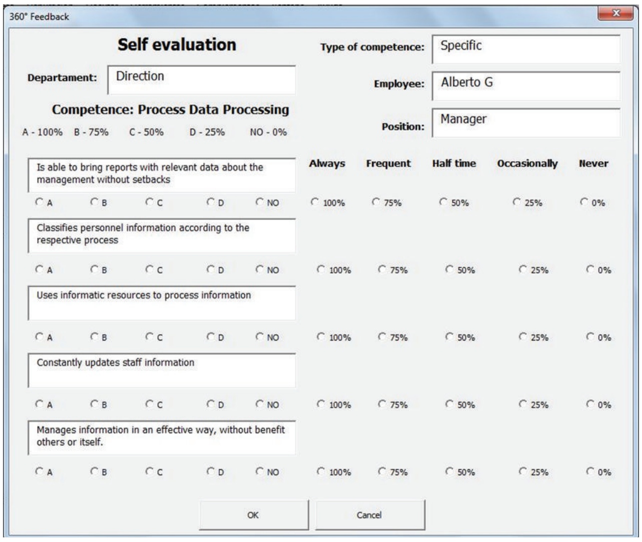

Figure 3: Questionnaire example.

(5) Data processing: most of the time data are processed by external consultants to preserve information confidentiality.

(6) Communicate 360° evaluation results to concerned people.

(7) The company will receive a consolidated report. This report will be received only by the employee.

In this work, 360 degree feedback methodology proposed by Alles [29] is applied under two different approaches: traditional 360° feedback and fuzzy logic 360° feedback. Likewise, there are some other substantial differences. (1) Data processing is performed by two software applications, each designed for its specific process. Both applications are able to select evaluators randomly and present questionnaires. From this point, there is another difference: (2) first application performs the evaluation in the traditional 360 degree feedback; the second application is an expert system that uses fuzzy logic into the questionnaires to perform evaluation. The third substantial difference, hence, is that (3) expert system does not require a human expert, except when they are designed. No external consultant is necessary anymore, since expert system achieves this objective too.

2.3. Fuzzy Logic Basis. Fuzzy logic is the mapping from an input measurement space to an output measurement space using linguistic variables. It gives the ability to model imprecision by incorporating qualitative components into a quantitative analysis.

Fuzzy logic systems have a narrow relationship with fuzzy logic concepts such as fuzzy sets and linguistic variables. The most popular fuzzy logic systems are Mamdani and Takagi-Sugeno.

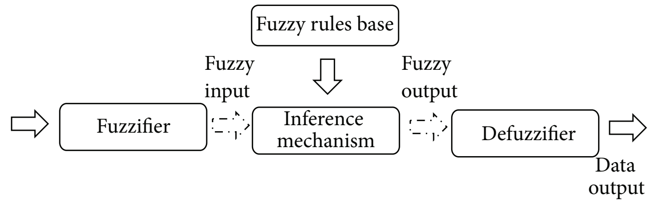

Figure 4: Mamdani general fuzzy logic system.

Mamdani fuzzy systems use 4 components (see Figure 4).

(i) Fuzzifier: Mamdani system inputs are typically numeric values, coming from some kind of sensor or being results of a process; to be able to operate this value, Mamdani systems translate this value into a special value that can be operated by the inference mechanisms. This translation is done by the fuzzifier, which converts numeric values into fuzzy values that represent the level of pertinence of the different variables of the system to the fuzzy sets.

(ii) Fuzzy inference mechanism: once the fuzzifier has translated the fuzzy values, these have to be processed to generate a fuzzy output. Inference mechanism task is to take fuzzy values and generate a fuzzy output based on a fuzzy rules base.

(iii) Fuzzy rules base is the way in which Mamdani fuzzy systems have to represent expertise and linguistic knowledge to solve the issue. It is a set of IF-THEN sentences, containing two parts each: antecedent and conclusion. In a Mamdani fuzzy system, antecedent and conclusion are given by linguistic expressions.

(iv) Defuzzifier: inference system output is a fuzzy output, so it cannot be interpreted by an external element which only could operate numeric data. To make it possible to operate this data, output is translated to numeric format, and this task is done by the defuzzifier, using one of different procedures such as gravity center or averaged centers.

Fuzzy Logic uses certain essential components to achieve its purpose.

Imprecision. Often the same term is used to describe imprecision and uncertainty in only slightly related areas of measurement. Imprecision in measurement is associated with a lack of knowledge. Imprecision as a probability form is associated with uncertainty about the future event occurrence. Imprecision in description, the imprecision type addressed by fuzzy logic, is connected with intrinsic or built-in imprecision that belongs to the event itself.

Fuzzy logic addresses the issues associated with an intrinsic imprecision rather than those directly concerned with measuring devices failures in the measurements accuracy.

Intrinsic imprecision is associated with a phenomenon properties description and not with properties measurement using some external device.

Ambiguity. There are close semantic relationships between the ambiguity idea and fuzziness; in fact, some fuzzy states can be highly ambiguous. Ambiguity connotes the property to have several but plausible and reasonable interpretations. These interpretations can have different belief states. Ambiguity in meaning is a common occurrence in natural languages.

Likelihood and Ambiguity. Fundamentally, the basic confusion between fuzzy logic and probability arises from the idea that they measure the same kind of uncertainty. In strictly semantic, as well as mechanistic, the two forms of uncertainty are different. Propositions in probability address the likelihood of an outcome for some discrete event. The event outcome either happens or does not happen. Propositions in fuzzy logic concern the degree to which an event occurred. While a probability outcome happens unequivocally, a fuzzy event occurrence may involve some degree of ambiguity or uncertainty.

Fuzzy Sets Components. Gregory [30] indicates that the fuzzy logic has two main components: membership functions and fuzzy rules. When using these components it is possible to move the experiences and human preferences from a qualitative description to a quantitative description.

Membership fuzzy functions can take different figures and forms, according the designer experiences and preferences. Typical functions are triangular, trapezoidal, S, Gamma, Gaussian, and exponential. On the other hand, the fuzzy rules are written as IF-THEN couples and reported in tabular form.

The four basic ways in which the fuzzy rules can be achieved are expert experiences and engineering knowledge, human behaviors, models based on a fuzzy system, and learning processes. These methods are not necessarily mutually exclusive.

Membership Functions. In classical set theory, something is completely included or not. This situation can be described by assigning a value of one to all the elements included in the set and the value of zero to the ones not included in it. The function that assigns these values is called "membership function." The fuzzy sets allow to describe the degree of membership of the object to the concept given by the labels, and allow to assign values between zero and one to the membership function (see Figure 5).

Mathematical Features of Fuzzy Sets. Main characteristics of the fuzzy sets are height, support, cutoff level-α, and nucleus.

Height. It is the highest degree of membership of the elements of the set; that is,

$$\text{Height}(A) = \max\{h \mid h = \mu_A(x), x \in X\}. \tag{18}$$

When the height of a fuzzy set is equal to 1 it is said that it is a normalized fuzzy set.

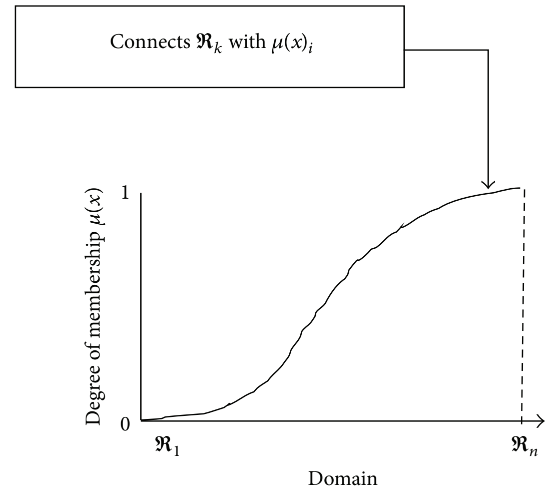

Figure 5: General structures in a fuzzy set.

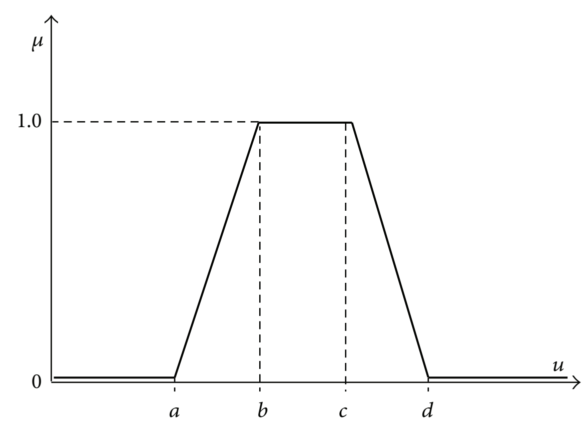

Figure 6: Trapezoidal type membership function.

Support. It is the number of elements whose degree of membership is not zero; that is,

$$\text{Sup}(A) = \{x \mid \mu_A(x) > O, x \in X\}. \tag{19}$$

Cutoff Level-α. It is the set of elements of X with a minimum degree α; that is,

$$A_\alpha = \{x \mid \mu_A(x) \geq \alpha, x \in X\}. \tag{20}$$

Nucleus. It is the set of elements of X with a degree of membership equal to 1; that is,

$$\text{Nucleus}(A) = \{x \mid \mu_A(x) = 1, x \in X\}. \tag{21}$$

Inclusion Functions in Fuzzy Sets. There are standard families for inclusion functions; the most frequent ones are trapezoidal, singleton, triangular, S, exponential, and π type.

Trapezoidal functions are defined by four points: a, b, c, and d (see Figure 6). This function is zero for values lower than "a" and higher than "d" and one between "b" and "c" and takes values in range $[0, 1]$ between "a" and "b" and between

"c" and "d." It is used in simple fuzzy systems, since it allows defining a fuzzy set with little information and computing membership function values in a simple way.

This function is common for microprocessor based systems since it can be encoded in a similar format as S functions, π functions, and triangular and singleton functions (e.g., if points b and c are combined the result is a triangular function). Trapezoidal function is defined as follows (see (22)):

$$S(u; a, b, c, d) = \begin{cases} 0, & u < a, \\ \left(\dfrac{u-a}{b-a}\right), & a \le u \le b, \\ 1, & b \le u \le c, \\ \left(\dfrac{d-u}{d-c}\right), & c \le u \le d, \\ 0, & u > d. \end{cases} \quad (22)$$

Trapezoidal functions are suitable to model properties in a range of values, stages, or levels (e.g., young, adult, elder, etc.). Modeling a triangular function can be done through the $b = c$ simplification. For an S function and singleton types (but not soft), $c = d = \max(U)$ and $a = b = c = d$ transformations can be applied, respectively.

Triangular function (T) can be defined as indicated in

$$T(u; a, b, c) = \begin{cases} 0, & u < a, \\ \dfrac{u-a}{b-a}, & a \le u \le b, \\ \dfrac{c-a}{c-b}, & b \le u \le c, \\ 0, & u > c. \end{cases} \quad (23)$$

T functions (see Figure 7) are appropriate for modeling properties with an inclusion value different from zero and for a narrow range of values around point b.

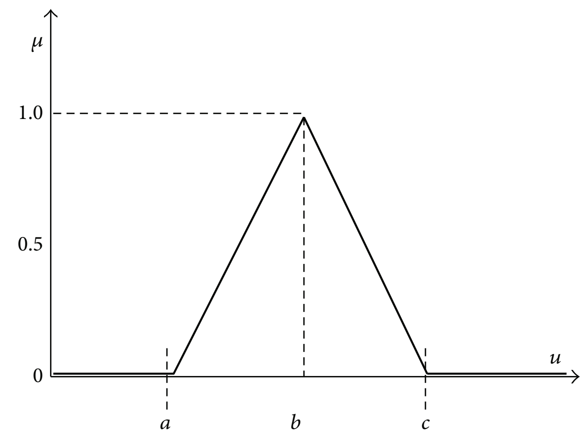

Figure 7: Type T (triangular) function.

Linguistic Variables. Linguistic variables take values from natural language, for example, much, little, positive, negative, and so forth. These words are considered as labels within the fuzzy set theory.

Even though linguistic variables aim to assign labels as variable values taken from natural language words, they will be able to assign numerical values too. Then, in the expression "temperature is cold," the variable "temperature" must be seen as a linguistic variable, since the value cold is assigned as a fuzzy set. However, this variable can also take numerical values such as "temperature is 4°C."

Fuzzy Rules. Fuzzy rules combine one or more input fuzzy sets, called premises, and associate them with an outcome fuzzy set, called consequence. The fuzzy set premise is associated using AND, OR, and so forth operators.

Defuzzification Process. There are two common methods of defuzzification process: gravity center (centroid) and maximum output. As is shown in Figure 8, both techniques produce different results [31].

Both techniques produce reasonable results when they are applied in specific fuzzy models. Gravity center is the most common method, because it combines evidence about rules and response fields are pondered by the total true degree. Gravity center is, essentially, the weighted average of the output membership function.

Centroid Computation. Centroid technique finds the balance point solution in fuzzy zone using the weighted average in the fuzzy region. Arithmetically, the procedure is formulated by

$$\Re = \frac{\sum_{i=0}^{n} d_i \cdot \mu_A(d_i)}{\sum_{i=0}^{n} \mu_A(d_i)}, \quad (24)$$

where d is the ith domain value and $\mu(d)$ is the true membership value at this point. Centroid or defuzzification with moments finds a point that represents the fuzzy set gravity center.

2.4. Fuzzy Logic Personnel Evaluation Model. A competence performance evaluation involves subjective viewpoints and evaluator preferences are reflected at the evaluation moment. Very often, evaluators express their perceptions in natural language terms. Nevertheless, as mentioned above, evaluation questionnaires constitute the performance evaluation support, and they are based on punctual values that do not reflect or approximate real viewpoints.

Therefore, it is desirable to have a flexible evaluation tool that facilitates imprecision, ambiguity, and subjectivity handling. In this purpose, fuzzy sets allow a suitable treatment.

The fuzzy logic model proposed is constituted as follows.

Linguistic Variables. Three linguistic variables have been defined, "Scale," "Frequency," and "Required Level."

"Scale" variable refers to the percentage (assigned by the evaluator) indicating how well the employee behavior matches the competence definition.

"Frequency" refers to the percentage obtained when the evaluator answers a question and "rethinks" his/her evaluation determining the number of times the behavior is manifested.

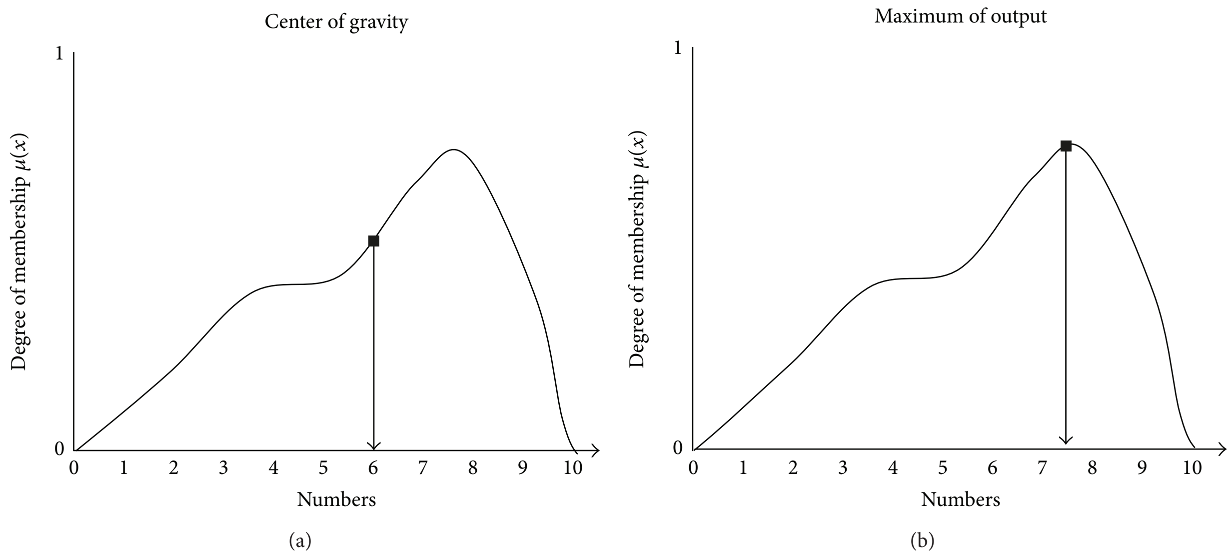

Figure 8: Defuzzification common methods.

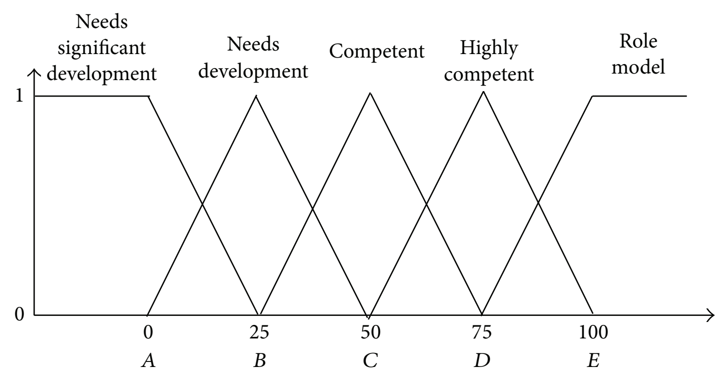

Figure 9: Fuzzy sets for linguistic variable "Scale."

"Required Level" refers the percentage expected by the organization; the individual must cover conduct according the competence definition.

Output Variables. They refer to the fit conduct qualification corresponding to the competence definition given in percentage. Under this consideration there are three cases, "needs to improve," "satisfies," and "exceeds."

Fuzzy Sets Representation. This model uses triangular inclusion functions to represent linguistic variables; the output variable was modeled with trapezoidal functions.

According to the expert, five fuzzy sets define the variable "Scale" possible values (see Figure 9), which are

(i) "needs significant development,"

(ii) "needs development,"

(iii) "competent,"

(iv) "highly competent,"

(v) "role model."

Likewise, there are four fuzzy sets to define the variable "Frequency" possible values (see Figure 10), which are

(i) "occasionally,"

(ii) "half time,"

(iii) "frequent,"

(iv) "always."

The "Required Level" variable was modeled through three possible fuzzy sets (see Figure 11), called

(i) "low,"

(ii) "average,"

(iii) "high."

The output variable has three cases which allow defining fuzzy sets (see Figure 12); these cases are

(i) "requires improvement,"

(ii) "complies,"

(iii) "exceeds."

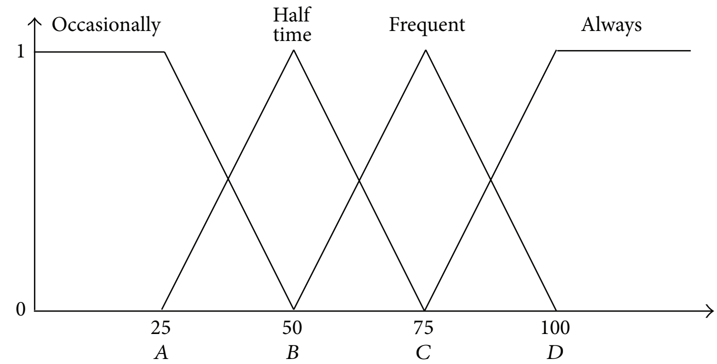

Figure 10: Fuzzy sets for linguistic variable “Frequency.”

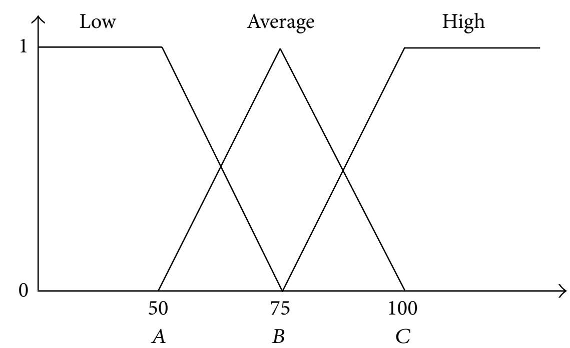

Figure 11: Fuzzy sets for linguistic variable “Required Level.”

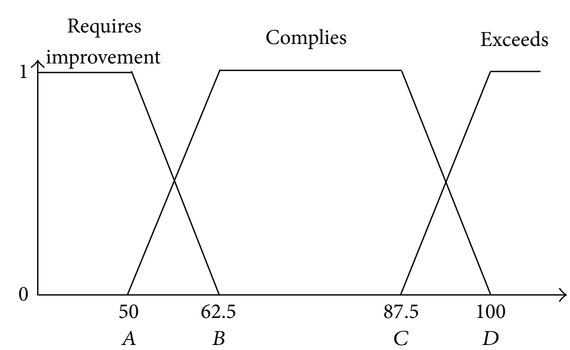

Figure 12: Fit qualification.

Fuzzy Rules. Fuzzy rules must consider all the combinations among input variables sets. Each combination will be associated with an output variable fuzzy set. Sixty fuzzy rules were created in this case, according to the opinion of an expert, who rigorously analyzed each set of inputs, determining the level of performance produced by each rule (see Table 1).

Fuzzification. The fuzzification process includes membership functions calculation for input variables and, then, uses the minimum-maximum criterion for variables activation.

Defuzzification. The defuzzification process will allow getting the final fit qualification; the proposed method is the gravity center (centroid) including the following four steps:

(1) divide total area in partial areas,

(2) calculate partial areas value,

(3) calculate each partial area centroid,

(4) calculate total centroid.

2.5. Computational Experiments. This section describes the use of the methodology using both traditional 360° feedback and 360° fuzzy logic feedback.

2.5.1. Application of the Expert System in a Real Company. The use of both methods was carried out in the administrative area of a Mexican manufacturing company, located in the state of Veracruz, Mexico, where administrative procedures require staff to be evaluated based on their performance annually. A branch of the organization chart, consisting of five different but related positions was selected to perform the 360° feedback evaluation process (see Figure 13).

2.5.2. Traditional 360° Methodology

(1) Identify cardinal and individual competences. To evaluate a position we will consider five cardinal competences and eight specific competences (see Table 2).

(2) Design the tool. This evaluation includes four questionnaires and each questionnaire includes five questions.

(3) Select an evaluator. Evaluation includes self-evaluation, boss evaluation, and peers evaluation. To choose evaluators and launch the process we will design and use the software; in this sense, the selection procedure is random.

(4) Execute the evaluation process with concerned people and evaluators. As an example, Table 3 shows self-evaluation values for cardinal competences.

Table 1: Fuzzy rules summary.

	SCALE																			
	Needs significant development Frequency				Needs development Frequency				Competent Frequency				Highly competent Frequency				Role model Frequency			
Required level	Occasional	Half time	Frequent	Always	Occasional	Half time	Frequent	Always	Occasional	Half time	Frequent	Always	Occasional	Half time	Frequent	Always	Occasional	Half time	Frequent	Always
Low	C (1)	C (4)	I (7)	I (10)	C (13)	C (16)	I (19)	I (22)	C (25)	C (28)	E (31)	E (34)	C (37)	C (40)	E (43)	E (46)	E (49)	C (52)	E (55)	E (58)
Average	C (2)	I (5)	I (8)	I (11)	C (14)	I (17)	I (20)	I (23)	I (26)	C (29)	C (32)	C (35)	C (38)	C (41)	C (44)	E (47)	C (50)	C (53)	C (56)	E (59)
High	I (3)	I (6)	I (9)	I (12)	I (15)	I (18)	I (21)	I (24)	I (27)	I (30)	C (33)	C (36)	I (39)	I (42)	C (45)	C (48)	I (51)	I (54)	C (57)	C (60)

I: requires improvement.
C: complies.
E: exceeds.

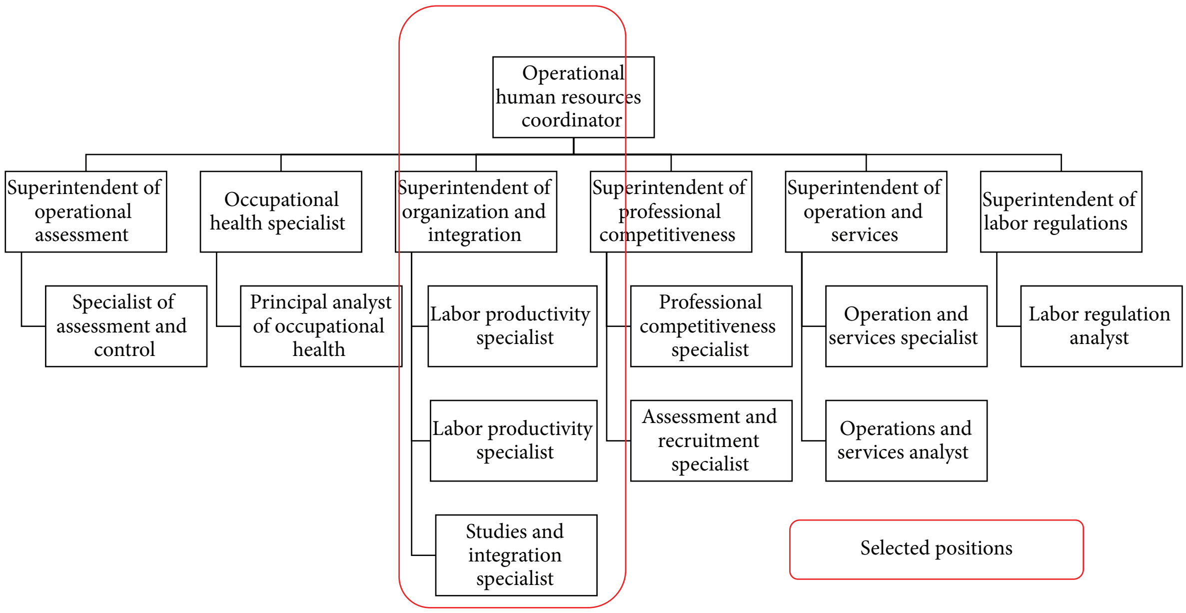

Figure 13: Organizational chart.

Table 2: Cardinal and specific competences.

Cardinal competences	Specific competences
(1) Work quality	(1) Planning and organization skills
(2) Tolerance to work under pressure	(2) Customer orientation
(3) Communication skills	(3) Productivity
(4) Contact modalities	(4) Technical credibility
(5) Analytical skills	(5) Innovation
	(6) Empowerment
	(7) Collaboration
	(8) Commitment level-personal discipline-productivity

(5) Data processing: software specifically designed for data processing to obtain the competence level scale value and frequency value was used; then we will average the results for each question (see Table 4). Finally, averages are compared with the Required Level. The same procedure will be used for specific competences treatment.

(6) Reports will be delivered only to the evaluated person. Comments and graphs will be printed in two reports: the first one will include cardinal competences and will be given to the company, while the second report will include specific competences and will be given to the employee.

(7) Communicate the 360° evaluation results to the concerned people.

2.5.3. Fuzzy Logic Model Implementation. (1) Choose an organizational department.

(2) Choose a post in the selected department.

(3) Choose a required competence in the post.

(4) Select one question in the questionnaire that evaluates the competence.

(5) Evaluator assigns values for input variables "Scale" and "Frequency," for example,

Scale = 62%

Frequency = 84%

The Required Level assigned by the company = 75%.

(6) Fuzzification process: compute the variable membership values corresponding to the variable Scale:

$$\mu_{\text{COMPETENT}}(\text{SCALE}) = \begin{cases} 0; & W \le B' \quad 0, \\ 1 - \dfrac{C' - W}{C' - B'}; & B' < W \le C' \quad 0, \\ 1 - \dfrac{W - C'}{D' - C'}; & C' < W < D' \quad 0.52, \\ 0; & D' \le W \quad 0, \end{cases}$$
$$\mu_{\text{HIGHLY-COMPETENT}}(\text{SCALE}) = \begin{cases} 0; & W \le C' \quad 0, \\ 1 - \dfrac{D' - W}{D' - C'}; & C' < W \le D' \quad 0.48, \\ 1 - \dfrac{W - D'}{E' - D'}; & D' < W < E' \quad 0, \\ 0; & E' \le W \quad 0. \end{cases} \tag{25}$$

Table 3: Self-evaluation values, cardinal competences.

(a)

	360° evaluation				Cardinal competencies			Self-evaluation		
	Work quality	Required level: 100	Tolerance to work under pressure	Required level: 75	Communication	Required level: 75	Contact modalities	Required level: 100	Analytic skills	Required level: 75
	Scale	Frequency	Scale	Frequency	Scale	Frequency	Scale	Frequency	Scale	Frequency
Ques. 1	75	100	100	100	100	25	75	100	75	25
Ques. 2	75	75	75	50	100	100	100	100	100	75
Ques. 3	100	50	100	100	75	100	100	75	100	75
Ques. 4	100	100	75	75	50	100	75	100	50	50
Ques. 5	75	100	50	25	25	75	50	25	100	100

(b)

Where	
Scale	Frequency
100%: A	100%: always
75%: B	75%: frequent
50%: C	50%: half time
25%: D	25%: occasional
0%: NO	0%: never

Table 4: Self-evaluation, cardinal competences treatment.

(a)

	360° evaluation						Cardinal competencies			Self-evaluation					
	Work quality	Required level: 100		Pressure tolerance	Required level: 75		Communication	Required level: 75		Contact modalities	Required level: 100		Analytic skills	Required level: 75	
	Scale	Frequency	Product	Scale	Frequency	Product	Scale	Frequency	Product	Scale	Frequency	Product	Scale	Frequency	Product
Ques. 1	75	100	75	100	100	100	100	25	25	75	100	75	75	25	18.75
Ques. 2	75	75	56.25	75	50	37.5	100	100	100	100	100	100	100	75	75
Ques. 3	100	50	50	100	100	100	75	100	75	100	75	75	100	75	75
Ques. 4	100	100	100	75	75	56.25	50	100	50	75	100	75	50	50	25
Ques. 5	75	100	75	50	25	12.5	25	75	18.75	50	25	12.5	100	100	100
	Average		71.25			61.25			53.75			67.5			58.75

(b)

Where	
Scale	Frequency
100%: A	100%: always
75%: B	75%: frequent
50%: C	50%: half time
25%: D	25%: occasional
0%: NO	0%: never

Compute the variable membership values corresponding to the variable Frequency:

$$\mu_{\text{FREQUENT}}(\text{FREQUENCY}) = \begin{cases} 0; & W \le B \quad 0, \\ 1 - \dfrac{C-W}{C-B}; & B < W \le C \quad 0, \\ 1 - \dfrac{W-C}{D-C}; & C < W < D \quad 0.64, \\ 0; & D \le W \quad 0. \end{cases} \tag{26}$$

$$\mu_{\text{ALWAYS}}(\text{FREQUENCY}) = \begin{cases} 0; & W \le C \quad 0, \\ 1 - \dfrac{D-W}{D-C}; & C < W \le D \quad 0.36, \\ 1; & D \le W \quad 0. \end{cases}$$

Compute the variable membership values corresponding to the variable Required Level:

$$\mu_{\text{AVERAGE}}(\text{REQUIREDLEVEL}) = \begin{cases} 0; & W \le A'' \quad 0, \\ 1 - \dfrac{B''-W}{B''-A''}; & A'' < W \le B'' \quad 1, \\ 1 - \dfrac{W-B''}{C''-B''}; & B'' < W < C'' \quad 0, \\ 0; & C'' \le W \quad 0. \end{cases} \tag{27}$$

The fuzzification process continues with variable activation, performed according to the min.-max. criterion (see (28), (29), (30), and (31)); this procedure allows identifying the membership values that will appear in the defuzzification process.

Rule 32 is

$$\begin{aligned} &\mu_{C\cap F\cap M}(62, 84, 75) \\ &\quad = \min\{\mu_C(62), \mu_F(84), \mu_M(75)\} \\ &\quad = \min\{0.52, 0.64, 1.00\} = 0.52. \end{aligned} \tag{28}$$

Rule 35 is

$$\begin{aligned} &\mu_{C\cap S\cap M}(62, 84, 75) \\ &\quad = \min\{\mu_C(62), \mu_S(84), \mu_M(75)\} \\ &\quad = \min\{0.52, 0.36, 1.00\} = 0.36. \end{aligned} \tag{29}$$

Rule 44 is

$$\begin{aligned} &\mu_{A\cap F\cap M}(62, 84, 75) \\ &\quad = \min\{\mu_A(62), \mu_F(84), \mu_M(75)\} \\ &\quad = \min\{0.48, 0.64, 1.00\} = 0.48. \end{aligned} \tag{30}$$

Table 5: Membership degree for activated variables.

Activated variable	Set, output variable	Membership degree
32	Requires improvement	0.52
35	Complies	0.36
44	Complies	0.48
47	Complies	0.36

Table 6: Membership degree for activated variables.

Activated variable	Fuzzy set	Membership degree
—	Exceeds	0
35, 44, 47	Complies	0.48
32	Requires improvement	0.52

Rule 47 is

$$\begin{aligned} &\mu_{A\cap S\cap M}(62, 84, 75) \\ &\quad = \min\{\mu_A(62), \mu_S(84), \mu_M(75)\} \\ &\quad = \min\{0.48, 0.36, 1.00\} = 0.36. \end{aligned} \tag{31}$$

The rules 32, 35, 44, and 47 are the activated variables; they have correspondence with a set in the output variable (see Table 5).

Three activated variables are in the "Obey" set; it is necessary to use the min.-max. criterion to select one value (see (32)):

$$\begin{aligned} \mu_C &= (62, 84, 75) \\ &= \vee\{\wedge\{\mu_C(62), \mu_S(84), \mu_M(75)\}, \\ &\qquad \wedge\{\mu_{AC}(62), \mu_F(84), \mu_M(75)\}, \\ &\qquad \wedge\{\mu_{AC}(62), \mu_S(84), \mu_M(75)\}\} \\ &= 0.48. \end{aligned} \tag{32}$$

The last membership degrees and activated variables are summarized as follows (see Table 6).

(7) Defuzzification process: this procedure includes five steps.

Divide the total area in partial areas (see Figure 14).

Compute the partial area values (see (33)):

$$\begin{aligned} (A_{\text{I}}) &= \frac{[0.52]^2 (62.5 - 50)}{2} = 1.69, \\ (A_{\text{II}}) &= [0.52][1 - 0.52](62.5 - 50) = 3.12, \\ (A_{\text{III}}) &= \frac{[0.48](62.5 - 50)}{2} = 3, \\ (A_{\text{IV}}) &= [0.48](87.5 - 62.5) = 12, \\ (A_{\text{V}}) &= [0.48][1 - 0.48](100 - 87.5) = 3.12, \\ (A_{\text{VI}}) &= \frac{[0.48]^2 (100 - 87.5)}{2} = 1.44. \end{aligned} \tag{33}$$

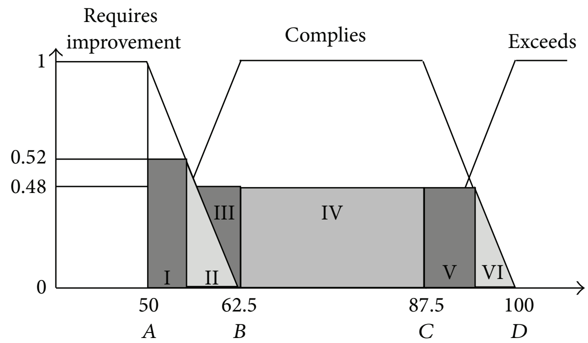

Figure 14: Partial areas.

Compute each partial area centroid (see (34)):

$$\text{Centroid } (A_{\text{I}}) = 50 + \frac{(62.5-50)(1-0.52)}{2} = 53,$$

$$\text{Centroid } (A_{\text{II}}) = 62.5 - \frac{2(62.5-50)[0.52]}{3} = 58.1666,$$

$$\text{Centroid } (A_{\text{III}}) = 62.5 - \frac{(62.5-50)[0.48]}{3} = 60.5,$$

$$\text{Centroid } (A_{\text{IV}}) = \frac{62.5+87.5}{2} = 75,$$

$$\text{Centroid } (A_{\text{V}}) = 87.5 + \frac{(100-87.5)(1-0.48)}{2} = 90.75,$$

$$\text{Centroid } (A_{\text{VI}}) = 100 - \frac{2(100-87.5)[0.48]}{3} = 96. \quad (34)$$

Calculate the total centroid (see (35)):

$$\begin{aligned} \text{CeT} &= ((1.69)(53) + (3.12)(58.16) + (3)(60.5) \\ &\quad + (12)(75) + (3.12)(90.75) + (1.44)(96)) \\ &\quad \times (1.69 + 3.12 + 3 + 12 + 3.12 + 1.44)^{-1} \\ &= \frac{1773.93}{24.37} = 72.79. \end{aligned} \quad (35)$$

(8) Competences questionnaires have more than one question. In this sense, each questionnaire will have as many fuzzy treatments as questions. At the end of the process, an average qualification for each competence will be obtained.

(9) Evaluation software and evaluation report. Intelligent evaluation systems have questionnaires that emulate human thought since it gives the option to answer questions using linguistic labels (see Figure 15). Once the evaluator has selected a label, it selects a numerical value. Final stage includes an evaluation report,which includes a summarized table with average qualifications for each competence.

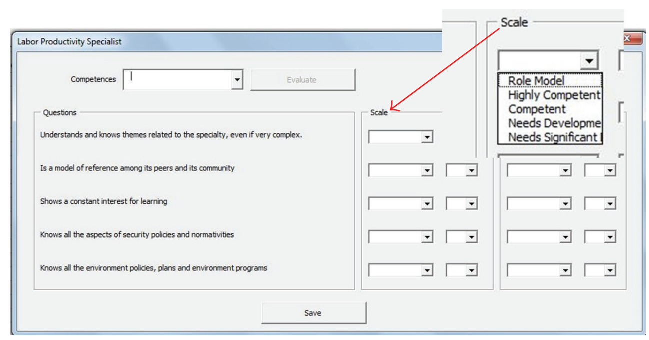

Figure 15: Evaluation questionnaire.

Table 7: Cardinal competences and required level.

Cardinal competences	Required level
Work quality	100%
Pressure tolerance	75%
Communication	75%
Contact modalities	100%
Analytic skill	75%

3. Results

3.1. 360° Methodology Application. A complete application includes four-position analysis (see Figure 13); five cardinal competences were developed using the job description (see Table 7). The first position has nine specific competences, while the second position has ten specific competences (see Table 8), the third position has eight competences, and finally the fourth position has ten competences. Required Levels were established with the company.

Applying the complete traditional methodology 360° to the first position, we concluded that the company must improve "work quality" and "contact modalities," since these competences obtained the major difference with the Required Level (see Table 9).

The individual report includes specific competences summary.

Table 8: Specific competences and required level.

Specific competences			
Position level I	Required level	Position level II	Required level
(1) Work team	100%	(1) Planning and organization skills	100%
(2) Negotiation	100%	(2) Negotiation	50%
(3) Personnel development	75%	(3) Initiative autonomy	100%
(4) Leadership	100%	(4) Leadership	100%
(5) Frankness-trustworthy-integrity	50%	(5) Frankness-trustworthy-integrity	50%
(6) Commitment	75%	(6) Empowerment	100%
(7) Collaboration	50%	(7) Strategic thinking	100%
(8) Coaching	75%	(8) Commitment level-personal discipline-productivity	100%
(9) Decision making	100%	(9) Making decisions	100%
		(10) Human Resources strategic development	50%

Table 9: Cardinal competences report.

	Cardinal competences				
	Work quality	Pressure tolerance	Communication	Contact modalities	Analytic skill
Self-evaluation	71.25	61.25	53.75	67.5	58.75
Peer	21.25	16.25	13.75	41.25	51.25
Head	25.00	43.75	17.50	15.00	16.25
360° weighted	39.17	40.42	28.33	41.25	42.08
Required level	100.00	75.00	75.00	100.00	75.00
Difference: required level, 360° weighted	60.83*	34.58	46.67	58.75*	32.92

*Competences with major difference.

Table 10: Specific competences report.

	Specific competences							
	Planning and organization ability	Client orientation	Productivity	Credibility technique	Innovation	Empowerment	Collaboration	Commitment level-personal discipline-productivity
Self-evaluation	63.75	43.75	60.00	26.25	72.50	25.00	37.50	22.50
Peer	48.75	61.25	56.25	48.75	41.25	37.50	63.75	62.50
Boss	12.50	18.75	17.50	13.75	6.25	5.00	15.00	13.75
360° weighted	41.67	41.25	44.58	29.58	40.00	22.50	38.75	32.92
Required level	75.00	50.00	100.00	75.00	100.00	50.00	100.00	100.00
Difference: required level, 360° weighted	33.33	8.75	55.42	45.42	60.00	27.50	61.25*	67.08*

*Competences with major difference.

Applying the complete traditional methodology 360° to the same post, we concluded that an employee must improve "collaboration" and "commitment level-personal discipline-productivity," since these competences obtained the biggest difference with the Required Level (see Table 10).

3.2. Fuzzy Logic Model Application. Applying the full fuzzy logic model evaluation to the first position, we concluded that the company must improve "communication" and "contact modalities," since these competences obtained the lower final qualification.

Employee must focus on "credibility technique" and "commitment level-personal discipline-productivity" (see Figure 16).

4. Discussion

Traditional methodology 360° indicates competences that the company and the employee must care. Fuzzy logic 360° methodology indicates the competences on which the company and the employees must focus their efforts but in addition gives a qualification. This qualification can be arranged and the lowest value will indicate which competences must be immediately attended.

According to Table 11, the traditional 360° and fuzzy logic methodologies conclude that the company must attend the cardinal competence "contact modalities" and the employee must focus on the specific competence "commitment level-personal discipline-productivity." However, fuzzy logic

Table 11: Comparison results.

Competences classification	Traditional 360° Methodology	Fuzzy Logic 360° Expert system
Cardinal	∗Work quality ∗**Contact modalities**	∗Communication: 56.67 ∗**Contact modalities:** 57.33
Specific	∗Collaboration ∗**Commitment level-personal discipline-productivity**	∗Technical Credibility: 58.33 ∗**Commitment level-personal discipline-productivity:** 59.67

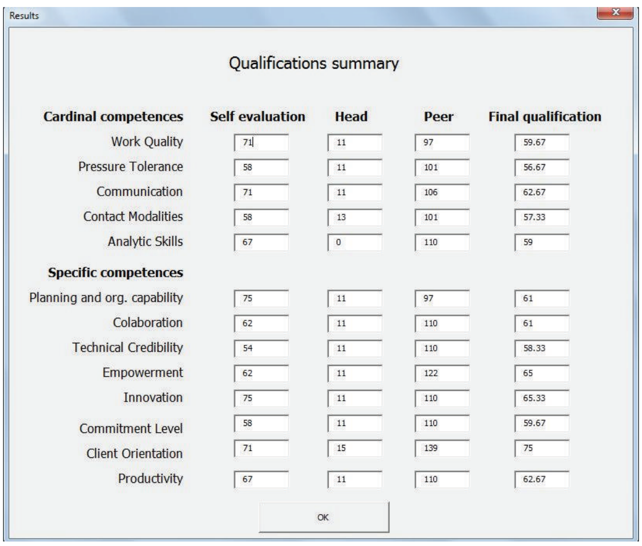

Figure 16: Qualifications summary.

method indicates that "contact modalities" must be attended after "communication," and "commitment level-personal discipline-productivity" must be attended after "technical credibility."

The traditional 360° system involves only two factors, "Scale" and "Frequency," and these are compared with the third factor "Required Level." On the other hand, fuzzy logic model can involve three factors like input variables.

Evaluation questionnaires of the traditional 360° methodology are filled with five possible percentages (100, 75, 50, 25, and 0). On the other hand, questionnaires in fuzzy logic expert system have adjustable values scales, allowing improved flexibility for the evaluator.

Thus, the main advantage in fuzzy logic expert system is the human thinking simulation, assigning labels as a qualification, and allowing subjective and ambiguity treatment.

5. Conclusions

Competences performance evaluation 360° is a complete system since it involves different viewpoints to appraise personnel performance. It allows better interpretations, since the evaluation responsibility falls in different evaluators. This kind of evaluation facilitates the competence concept comprehension, and Required Levels are assimilated. Nevertheless, it is a rigid system because the questionnaire filling procedure is strict, since these were designed to assign fixed values.

Fuzzy logic competences evaluation expert system includes complex analysis, due to identification and modeling input and output variables. However, its main advantage is the ambiguity and subjectivity handling, since the evaluator can assign words to stand a qualification. This system is flexible because numerical adjustable values can be assigned to behaviors. Graphical interpretation helps to obtain suitable feedback. Even more, final processing reports can be obtained easier and faster. Therefore, it represents an excellent tool for competences monitoring, given the importance that the staff appraisal process has for human resource management, in the areas of recruitment and selection, job evaluation, identification of training needs, and so forth, and the value that results from having nonsubjective and bias-free assessments.

The application of an expert system to performance evaluation in a Mexican manufacturing company allows knowing its effectiveness against traditional techniques.

This work brings innovative contributions to soft computing and human resources management solutions, finding new ways to apply artificial intelligence techniques by means of computer applications to processes that typically were performed by humans.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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