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Computing with words for hierarchical competency based selection of personnel in construction companies

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ABSTRACT

As part of human resource management policies and practices, construction firms need to define competency requirements for project staff, and recruit the necessary team for completion of project assignments. Traditionally, potential candidates are interviewed and the most qualified are selected. Applicable methodologies that could take various candidate competencies and inherent uncertainties of human evaluation into consideration and then pinpoint the most qualified person with a high degree of reliability would be beneficial. In the last decade, computing with words (CWW) has been the center of attention of many researchers for its intrinsic capability of dealing with linguistic, vague, interdependent, and imprecise information under uncertain environments. This paper presents a CWW approach, based on the specific architecture of Perceptual Computer (Per-C) and the Linguistic Weighted Average (LWA), for competency based selection of human resources in construction firms. First, human resources are classified into two types of main personnel: project manager and engineer. Then, a hierarchical criteria structure for competency based evaluation of each main personnel category is established upon the available literature and survey. Finally, the perceptual computer approach is utilized to develop a practical model for competency based selection of personnel in construction companies. We believe that the proposed approach provides a useful tool to handle personnel selection problem in a more reliable and intelligent manner.

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1. Introduction

Human resource management (HRM) is defined as the processes that organize, manage and lead a project team [1]. It contributes to the success of the project [2,3] and creates a competitive advantage for the organization [4,5]. The HRM policies, processes, and practices in the construction company are in some way supportive of project-oriented working and are different from more traditional HRM processes and practices [6], which are designed for the classically managed organization. While in classically managed organizations, the emphasis is not on projects but instead on routine products and services where the job requirements are well defined and stable [7], in competency-based HRM, practices and policies are designed, developed and implemented based on personnel competencies in order to support the integration of human resource management. The latter forms a solid basis, which unifies the different steps of human resource management.

The project team is comprised of appropriate people with assigned roles and responsibilities for completing the project [1]. Project team members may also be referred to as the project staff or personnel [1,7]. Developing the project team improves the people skills, technical competencies, and overall team environment and project performance [8], which is a critical factor for project success [9,10]. Effective team development strategies and activities are expected to increase the team's performance, which increases the likelihood of meeting project objectives [11]. The degree or extent of this impact may vary, depends on certain factors such as project type, characteristic, and organizational context. If project team members do not possess required competencies, performance can be jeopardized [1]. Competency is the knowledge, skills, and behaviors a person needs to fulfill his or her role [12]. Assessing competencies, skills, and abilities, and knowing personality traits and key behaviors of individuals increase the chances of choosing a team that has the potential to succeed [8].

Traditionally, an expert interviews the candidates for job positions, and the best person is selected based on the capability analysis. The statistical techniques support the engaging decision through the arrangement of test scores and the measure of accomplishment for the candidate [12]. However, the process is often ambiguous, biased, and lacking in accuracy [13]. In contrast, in competency-based selection procedure, overall competencies of personnel are evaluated by the competency framework established

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for each specific job class. Therefore, this procedure is carried out for each class of jobs and careers rather than tasks and duties, which definitely leads to the fair evaluation of personnel.

As part of project HRM policies and practices, construction firms need to define competencies requirement for all project personnel and obtaining the team necessary to complete project assignments. Therefore, the purpose of this research is to construct and practice a competency based model for selecting personnel in construction companies, which are classified into two types of main personnel: project manager and engineer. A survey is undertaken to develop the competency criteria model of each main personnel. With the consideration of the main personnel competencies, we develop a CWW model based on the specific architecture of Perceptual Computer and the Linguistic Weighted Average for competency based selection of personnel in construction companies, where all linguistic terms are characterized by the interval type-2 fuzzy sets (IT2 FSs), directly exploited from the perception of a group of experts.

The rest of this paper is organized as follows: in Section 2, some recent literature on personnel selection problem is reviewed. In Section 3, some basic concepts, definitions and methods for IT2 FSs are briefly reviewed. In Section 4, some background and technical materials about CWW in decision-making are reviewed. We also go into more details about the Perceptual Computer concept and Linguistic Weighted Average method. In Section 5, the complete procedure for handling the human resource selection problem is considered. In Section 6, we validate the proposed methodology for personnel selection based on empirical example. In Section 7, we discuss the conclusion.

2. Literature review

The contemporary employee selection is a complex decision making process that is expected to be capable of placing the right employees in the right jobs at the right time. To date, so many tools and techniques have been utilized to cope with this specific decision making problem. Lai [14] described the employee selection process as a multi-objective decision making problem. Iwamura and Lin [15] explained that the employee selection process requires the accomplishment and aggregation of different factors. Golec and Kahya [16] presented a comprehensive hierarchical structure for selecting and evaluating a right employee. The process of matching an employee with a certain job is performed through a fuzzy model.

Korkmaz et al. [17] presented an Analytic Hierarchy Process (AHP) and two sided matching based Decision Support System (DSS) to assist detailers. Labib et al. [18] also suggested an employee selection process that uses the AHP. Gungor et al. [19] proposed a personnel selection system based on fuzzy AHP for dealing with both qualitative and quantitative criteria.

Drigas et al. [20] presented an expert system using Neuro-Fuzzy techniques that investigate a corporate database of unemployed and enterprises profile data for evaluation of the unemployed at certain job position. Shahhosseini and Sebt [21] presented a two-stage model for competency based selection and assignment of human resources to construction projects based on fuzzy AHP and ANFIS. Lin [22] developed a job placement intervention by taking into account the fuzzy assessment and a mixed integer-programming model to fulfill the efficient fit from the right policy. Strnad and Guid [23] presented a new fuzzy-genetic analytical model for the problem of project team formation. They used a special adaptation of island genetic algorithm with mixed crossover to optimize the selection of multiple project teams.

Polychroniou and Giannikos [24] presented a fuzzy multiple criteria decision making (MCDM) methodology based on the TOPSIS multi criteria decision tool and the algorithm presented by Karsak and Slocum [25] for selecting employees. Kelemenis and Askounis [26] and Kelemenis et al. [27] also presented a fuzzy TOPSIS for the ranking of the personnel alternatives. Lazarevic [28] presented a two-level employee selection fuzzy model to reduce the subjective judgments in the process of distinguishing between an appropriate and inappropriate employee for a job position.

As seen in literature, there are two main phases for establishing personnel selection models: developing the decision making hierarchy and selecting the methodology to be used. The former employee selection problem studies have developed decision making criteria based on job analysis. In addition, competency criteria hierarchies that have been studied in literatures are for general employees, and personnel of construction companies are not investigated in specific.

MCDM techniques have been noticeably utilized for solving this type of problems so far. It should be noted that these techniques, in spite of being implemented successfully in many problems and environments, might contribute to the imprecise judgments of decision makers since the experiences and judgments of humans are naturally presented by linguistic and vague patterns [29]. Consequently, many researchers have provided evidence that fuzzy MCDM techniques demonstrate relatively more convincing results compared to the MCDM methods [29]. Similarly, interval type-2 fuzzy sets could have wide applications in MCDM techniques since they provide us with an effective tool to deal with linguistic patterns, data imprecision and knowledge deficits.

3. Preliminaries

In recent years, researchers have shown growing interests in type-2 fuzzy sets to handle the systems with lots of uncertainties in design and implementation processes. Type-2 fuzzy sets, originally introduced by Zadeh [30], provide additional design degree of freedom to deal with uncertainties. To date, due to high computational cost and complexity of using general type-2 fuzzy sets, interval type-2 fuzzy sets have been received much more attention [31]. In this section, some basics and definitions are reviewed to make this paper more self-contained.

3.1. Interval type-2 fuzzy sets

In this section, we briefly review basic concepts and some definitions of type-2 fuzzy sets and interval type-2 fuzzy sets from Mendel et al. [31].

Definition 3.1.1. [31] A general type-2 fuzzy set, denoted $\tilde{A}$, can be expressed in the universe of discourse X by a type-2 membership function $\mu_{\tilde{A}}(x, u)$, shown as follows:

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x, u)) | \forall x \in X, \forall u \in J_x \subseteq [0, 1], 0 \leq \mu_{\tilde{A}}(x, u) \leq 1\}, \quad (1)$$

in which x is a *primary variable*, J_x is a *primary membership function*, u is a *secondary variable*, and $\mu_{\tilde{A}}(x, u)$ is a *secondary membership function*. A type-2 fuzzy set $\tilde{A}$ can also be represented as follows:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \frac{\mu_{\tilde{A}}(x, u)}{(x, u)}, \quad (2)$$

where $J_x \subset [0,1]$ and $\int \int$ denotes union in a continuous universe of discourse over all admissible x and u. In case of discrete universe of discourse, $\int$ can be replaced by $\sum$.

Definition 3.1.2. [31] For a general type-2 fuzzy set $\tilde{A}$, when all $\mu_{\tilde{A}}(x, u) = 1$ then $\tilde{A}$ is an interval type-2 fuzzy set which can be regarded as a special case of a general type-2 fuzzy set. In this case, the third dimension of general type-2 FS conveys no new

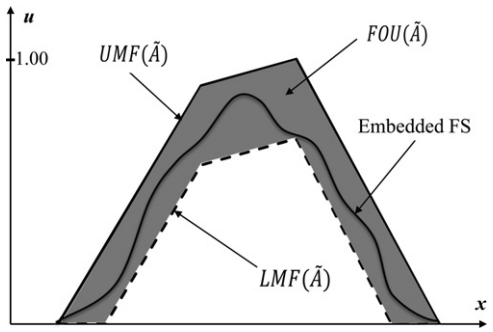


Fig. 1. UMF (Solid), LMF (dashed), FOU (shaded) and an embedded T1 FS (wavy line) for IT2 FS $\tilde{A}$.

information and is no longer needed. IT2 FSs can be represented as follows:

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x}\frac{1}{(x,u)}, \tag{3}$$

where $J_x \subset [0,1]$. Union of all of the primary memberships, called *footprint of uncertainty* of $\tilde{A}$ [FOU($\tilde{A}$)], characterizes the uncertainty about $\tilde{A}$:

$$\mathrm{FOU}(\tilde{A}) = \bigcup_{x\in X} J_x, \tag{4}$$

$$\tilde{A} = \frac{1}{\mathrm{FOU}(\tilde{A})}. \tag{5}$$

Definition 3.1.3. [31] Uncertainty in the primary memberships of an IT2 FS is a bounded region between the *upper membership function* (UMF) associated with the upper bound of FOU and the *lower membership function* (LMF) associated with the lower bound of FOU as shown in Fig. 1. The UMF denoted $\bar{\mu}_{\tilde{A}}(x)\,\forall x\in X$ and the LMF denoted $\underline{\mu}_{\tilde{A}}(x)$, $\forall x\in X$ are type-1 membership functions, respectively, i.e.,

$$\bar{\mu}_{\tilde{A}}(x) = \overline{FOU(\tilde{A})}, \tag{6}$$

$$\underline{\mu}_{\tilde{A}}(x) = \underline{FOU(\tilde{A})}. \tag{7}$$

Note that for an IT2 FS, $J_x = [\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)], \forall x\in X$.

Definition 3.1.4. [31] An *embedded* T1 FS A_e, as shown in Fig. 1, has N elements in the discrete universes of discourse $X = \{x_1, x_2, \ldots, x_N\}$ and U, where the A_e contains exactly one element from $J_{x_1}, J_{x_2}, \ldots,$ and J_{x_N}, namely $u_{x_1}, u_{x_2}, \ldots,$ and u_{x_N}, i.e.,

$$A_e = \sum_{i=1}^{N}\frac{u_i}{x_i}, \tag{8}$$

where $u_i \in J_x \subset U = [0,1]$. UMF and LMF are examples of embedded T1 FS A_e.

Definition 3.1.5. [32] The centroid $c(A)$ of a T1 fuzzy set A is defined as follows:

$$c(A) = \frac{\sum_{i=1}^{N} x_i\mu_A(x)}{\sum_{i=1}^{N}\mu_A(x)}. \tag{9}$$

The centroid $C(\tilde{A})$ of an IT2 FS $\tilde{A}$ is the union of the centroids of all its embedded T1 FSs A_e as follows:

$$C_{\tilde{A}} = \bigcup_{\forall A_e} c(A_e) = [c_l(\tilde{A}), c_r(\tilde{A})], \tag{10}$$

where $\cup$ is the union operation, and $c_l(\tilde{A})$ and $c_r(\tilde{A})$ are the minimum and maximum values of all centroids, respectively, which can be computed efficiently using EKM algorithm [33]. The average

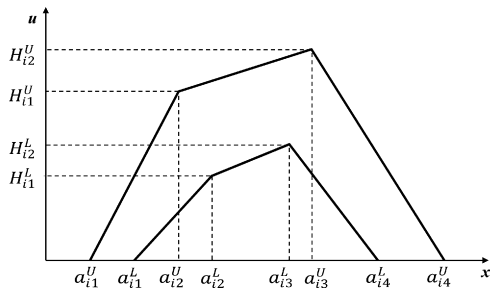


Fig. 2. Trapezoidal IT2 FS $\tilde{A}_i$.

centroid of $\tilde{A}$, $c(\tilde{A}) = (c_l(\tilde{A}) + c_r(\tilde{A}))/2$, is also defined as the center of the centroid of $\tilde{A}$, $C_{\tilde{A}}$.

Definition 3.1.6. [34] The Jaccard similarity measure, $s_J(\tilde{A},\tilde{B})$ between two IT2 FSs of $\tilde{A}$ and $\tilde{B}$ is defined as follows:

$$s_J(\tilde{A},\tilde{B}) = \frac{\int_X \min(\bar{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{B}}(x))dx + \int_X \min(\underline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{B}}(x))dx}{\int_X \max(\bar{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{B}}(x))dx + \int_X \max(\underline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{B}}(x))dx}. \tag{11}$$

In case of discrete universe of discourse, $\int$ can be replaced by $\sum$.

In this paper, trapezoidal interval type-2 sets are used for representing words. Trapezoidal interval type-2 fuzzy sets could be characterized with respect to the reference points on the X-axis and the heights of middle points of upper and lower membership functions. Therefore, trapezoidal IT2 FS $\tilde{A}_i$ can be represented as $\tilde{A}_i = (\tilde{A}_i^U, \tilde{A}_i^L) = ((a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U; H_{i1}^U, H_{i2}^U), (a_{i1}^L, a_{i2}^L, a_{i3}^L, a_{i4}^L; H_{i1}^L, H_{i2}^L))$, where $\tilde{A}_i^U$ and $\tilde{A}_i^L$ denote the UMF and LMF of IT2 FS, respectively, $H_{ij}^U \in [0,1]$ denotes the membership function value of the point $a_{i(j+1)}^U$, $1\le j\le 2$ and $1\le i\le n$ on the UMF of the $\tilde{A}$, and $H_{ij}^L \in [0,1]$ can be defined similar to H_{ij}^U as shown in Fig. 2.

3.2. Arithmetic operations between trapezoidal interval type-2 fuzzy sets

In this section, we briefly review some arithmetic operations for trapezoidal IT2 FSs from [35]. Let $\tilde{A}_1$ and $\tilde{A}_2$ be as follows:

$$\begin{aligned}\tilde{A}_1 &= (\tilde{A}_1^U, \tilde{A}_1^L)\\ &= ((a_{11}^U, a_{12}^U, a_{13}^U, a_{14}^U; H_{11}^U, H_{12}^U), (a_{11}^L, a_{12}^L, a_{13}^L, a_{14}^L; H_{11}^L, H_{12}^L)),\end{aligned}$$

$$\begin{aligned}\tilde{A}_2 &= (\tilde{A}_2^U, \tilde{A}_2^L)\\ &= ((a_{21}^U, a_{22}^U, a_{23}^U, a_{24}^U; H_{21}^U, H_{22}^U), (a_{21}^L, a_{22}^L, a_{23}^L, a_{24}^L; H_{21}^L, H_{22}^L)).\end{aligned}$$

Definition 3.2.1. The addition operation between the trapezoidal interval type-2 fuzzy $\tilde{A}_1$ and $\tilde{A}_2$ is defined as follows:

$$\begin{aligned}\tilde{A}_1 \oplus \tilde{A}_2 = ((&a_{11}^U + a_{21}^U, a_{12}^U + a_{22}^U, a_{13}^U + a_{23}^U, a_{14}^U + a_{24}^U; \min(H_{11}^U, H_{21}^U),\\ &\min(H_{12}^U, H_{22}^U)), (a_{11}^L + a_{21}^L, a_{12}^L + a_{22}^L, a_{13}^L + a_{23}^L, a_{14}^L + a_{24}^L;\\ &\min(H_{11}^L, H_{21}^L), \min(H_{12}^L, H_{22}^L))).\end{aligned} \tag{12}$$

Definition 3.2.2. The multiplication operation between the trapezoidal interval type-2 fuzzy $\tilde{A}_1$ and crisp value λ is defined as follows:

$$\begin{aligned}\lambda\tilde{A}_1 = ((&\lambda a_{11}^U, \lambda a_{12}^U, \lambda a_{13}^U, \lambda a_{14}^U; H_{11}^U, H_{12}^U),\\ &(\lambda a_{11}^L, \lambda a_{12}^L, \lambda a_{13}^L, \lambda a_{14}^L; H_{11}^L, H_{12}^L)).\end{aligned} \tag{13}$$

3.3. α-Cuts and decomposition theorem

Given a T1 FS A defined on its universe of discourse X, for any number $\alpha \in [0, 1]$, the α-cut of A, $A(\alpha)$, is the crisp set [36]:

$$A(\alpha) = \{x | \mu_A(x) > \alpha\} \quad \forall x \in X. \tag{14}$$

Definition 3.3.1. *α-Cut decomposition theorem*: Let $Y = f(X_1, \ldots, X_n)$ be an arbitrary crisp function, where X_i ($i = 1, \ldots, n$) is a T1 FS whose domain is D_{X_i} and the α-cut is $X_i(\alpha)$. Then, under Zadeh's extension principle, it is defined as [37]:

$$Y(\alpha) = f(X_1(\alpha), \ldots, X_n(\alpha)), \tag{15}$$

and the height of Y is equals to the minimum height of all X_i ($i = 1, \ldots, n$). For the proof, see [37].

4. Computing with words in decision making

Decision making can be seen as a complex human mental process of selecting the best alternative among different scenarios [38]. This remarkable, yet ordinary capability of humans originates from the ability to perform a wide variety of mental and physical tasks by means of manipulating different perceptions without needing to implement either precise measuring or computing with numbers or symbols [39,40]. So far, many precision-based methods and trends have been developed for implementing decision making processes in real-world applications where in most of the situations, a decision must be taken by the decision maker with regard to more than one single clear criterion. This situation refers to the so-called multiple criteria decision making. In decision making, we often confront with uncertain environments, a lack of precise information, and linguistic evaluations provided by experts. In many cases, it is unreasonable to impel decision makers (DMs) to give precise numerical evaluations by using their subjective perceptions, since the actual human decision making and preference processes are uncertain due to the deficit knowledge of DMs and intrinsic complexity of the problem [41]. Consequently, it is more realistic to provide DMs with the tool of linguistic terms for representing the rating values and the relative importance of the criteria. In order to overcome these difficulties, fuzzy set theory [42] has been utilized to deal with natural language propositions and uncertain nature of information, and Bellman and Zadeh [43] extended the classical decision making into fuzzy environment to deal with aforementioned uncertainties.

In 1996 and 1999, Zadeh [39,44] proposed the paradigm of "Computing with words" (CWW). According to Zadeh [39], CWW is "a methodology in which the objects of computation are words and propositions drawn from a natural language." Also, Zadeh [39] proposed the major imperatives for CWW as "when the available information is too imprecise to justify the use of numbers, and second, when there is a tolerance for imprecision which can be exploited to achieve tractability, robustness, low solution cost, and better rapport with reality.", which are definitely related to the concepts of granules [45], and linguistic variable [30,46,47], as described in [40]. It is worthy to note that Zadeh [39] equated fuzzy logic with CWW as an implementable and reasonable framework for dealing with linguistic variables and the interaction of humans and computers by using words. In recent years, CWW methodology has been a great field of research, and it has been applied to decision making problems in so many environments. For a more general view on CWW, its application, and existing literature, see [40,48–50].

In classical fuzzy decision making problems, the main steps are to establish the required criteria, to define the experts by which the problems can be evaluated, and to select the best alternative. Although, there have been so many proposed models and trends for the last step, all of them consist of same two phases: an *aggregation phase*, which is to obtain the overall performance of each alternative, and an *exploitation phase*, which is to select the best alternative [40]. Herrera and Herrera-Viedma [51] also argued that in linguistic decision making, it is imperative to present two prior steps before aggregation and exploitation phases, which are: *The choice of the linguistic term set with its semantics*, and *the choice of the aggregation operator for linguistic variables*.

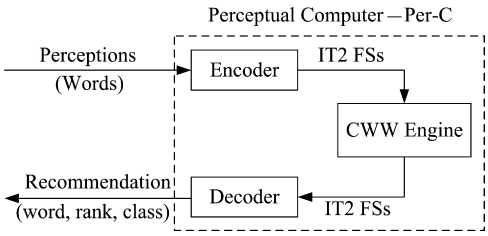


Fig. 3. Conceptual structure of the Perceptual Computer [37].

So far, there have been many methodologies developed for the CWW paradigm as a result of being a broad general concept open to different interpretation and trends. Herrera et al. [40] pointed out that the main existing computational models for linguistic aggregation in decision making field could be categorized as follows:

(1) Linguistic computational model based on membership functions [52–55].
(2) Linguistic computational model based on type-2 fuzzy sets [50,56–59].
(3) Linguistic symbolic computational models based on ordinal scales
   (a) Linguistic symbolic computational model based on ordinal scales and max–min operators [60–63].
   (b) Linguistic symbolic computational model based on convex combination [64].
   (c) Linguistic symbolic computational model based on virtual linguistic terms [65].
   (d) 2-Tuple linguistic computational model: a symbolic model extending the use of indexes [66].

A current trend for developing the CWW is to construct the richer models based on type-2 fuzzy linguistic semantic models. In the last decade, many researchers have justified the usage of IT2 FSs in CWW. Each IT2 FS can be viewed as an aggregation of type-1 fuzzy sets, and therefore they have the capacity to capture the inherent uncertainty of words, impreciseness of information, and subjective expert opinions and knowledge. Mendel [57] pointed out "*words mean different things to different people and so are uncertain. We therefore need a FS model for a word that has the potential to capture its uncertainties, and an IT2 FS should be used as a FS model of a word.*" In addition, Turksen [50] noted that "*Type 1 representation is a 'reductionist' approach for it discards the spread of membership values by averaging or curve fitting techniques and hence, camouflages the 'uncertainty' embedded in the spread of membership values. Therefore, Type 1 representation does not provide a good approximation to meaning representation of words and does not allow computing with words a richer platform.*", and hence, it is suggested to use IT2 FSs in CWW [57,67]. In this paper, we center our attention into the application of Perceptual Computer (Per-C) [56] in human resource selection, which is established upon IT2 FS to represent a word.

4.1. Perceptual Computer

In 2001, Mendel [49] proposed a specific architecture, shown in Fig. 3, for making subjective judgments by CWW. It is called *Perceptual Computer* (Per-C). The Per-C has been established upon IT2

FSs to have the potential of capturing word's uncertainties, which are at least *intrapersonal* uncertainty, and *interpersonal* uncertainty [57]. The former deals with the uncertainty that a person has about the word, and the latter emphasize that a word can be interpreted differently by a group of people. As depicted in Fig. 3, the Per-C consists of three main components. The *Encoder* maps the human perceptions expressed by words into IT2 FSs, which constitute the application-based *codebook* using for the interaction of human and computer. The encoding problem has been considered in [57,68–70]. The *decoder* transforms the IT2 FS outputs of *CWW Engine* to a word, rank, or class, which can be fulfilled by means of different methods. Wu and Mendel [34] compared the various methods of decoding problem. The *CWW Engine* maps the IT2 FSs into IT2FSs by means of *Perceptual Reasoning (PR)* method [58] for rule-based problems and *Linguistic Weighted Average (LWA)* method [37] for MCDM problems. We go in into more details of LWA in the following, inasmuch as human resource selection actually is a MCDM problem.

4.2. Linguistic Weighted Average (LWA)

Definition 4.2.1. The *weighted average* (WA), possibly the most widely used form of aggregation in MCDM problems, for set of criteria $C = \{C_1, C_2, \ldots, \text{and } C_n\}$, is defined as

$$y = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i}, \tag{16}$$

in which x_i is the evaluating value of the criterion C_i, and w_i is the associated weight of C_i that acts upon x_i.

Definition 4.2.2. The *interval weighted average* (IWA) for criteria $C = \{C_1, C_2, \ldots, \text{and } C_n\}$, is defined as

$$Y_{IWA} = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i} = [Y^l_{IWA}, Y^r_{IWA}], \tag{17}$$

where $X_i = [a_i, b_i]$, $i = 1, \ldots, n$, and $W_i = [c_i, d_i]$, $i = 1, \ldots, n$ represent the uncertainty bounds associated with the evaluating value and the weight of the C_i. As it is seen from Eq. (17), Y_{IWA} is also an interval, which can be completely determined by its two endpoints Y^l_{IWA}, and Y^r_{IWA}, where

$$Y^l_{IWA} = \min_{\substack{\forall X_i = [a_i, b_i] \\ \forall W_i = [c_i, d_i]}} \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i}, \tag{18}$$

$$Y^r_{IWA} = \max_{\substack{\forall X_i = [a_i, b_i] \\ \forall W_i = [c_i, d_i]}} \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i}. \tag{19}$$

In the last few years, several efficient algorithms have been developed that can easily compute the variables Y^l_{LWA}, and Y^r_{LWA}. In 2001, Karnik and Mendel [71] proposed an iterative procedure for performing Eqs. (18) and (19), entitled Karnik–Mendel (KM Algorithm), which has been received so much attentions since then. Later in 2009, Wu and Mendel [33] proposed the Enhanced Karnik–Mendel procedure (EKM algorithm) to reduce the computational cost of recursive KM algorithm. In addition, there are several other more efficient algorithms, e.g., iterative algorithm with stop condition (IASC) [72]. A comprehensive comparative study of the mentioned algorithms proposed for calculating Y^l_{LWA}, and Y^r_{LWA} values has been provided in [73].

Definition 4.2.3. The *fuzzy weighted average* (FWA) [74–78] for criteria $C = \{C_1, C_2, \ldots, \text{and } C_n\}$, is defined as

$$Y_{FWA} = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i} = f(X_1, \ldots, X_n, W_1, \ldots, W_n), \tag{20}$$

where W_i and X_i, $i = 1, \ldots, n$, are T1 fuzzy sets. It is important to note that in Eq. (20), Y_{FWA} cannot be computed using multiplication, addition, and division operations; and is just a symbolic way of representing Y_{FWA}. Instead, Liu and Mendel [78] proposed the using of α-cut decomposition theorem to compute Y_{FWA} efficiently. In this way, each α-cut on Y_{FWA}, $\alpha \in [0, h_{\max}]$, is the IWA computed interval of the corresponding α-cuts on W_i and X_i, $i = 1, \ldots, n$, as follows:

$$X_i(\alpha) = [a_i(\alpha), b_i(\alpha)], \quad i = 1, \ldots, n, \tag{21}$$

$$W_i(\alpha) = [c_i(\alpha), d_i(\alpha)], \quad i = 1, \ldots, n, \tag{22}$$

$$Y_{FWA}(\alpha) = Y_{IWA}(\alpha) = [Y^l_{IWA}(\alpha), Y^r_{IWA}(\alpha)], \tag{23}$$

where $\alpha \in [0, h_{\min}]$ which is discretized into $\{\alpha_1, \ldots, \alpha_m\}$, $h_{\min}$ is a minimum value of the heights of all W_i and X_i, $i = 1, \ldots, n$; and $Y^l_{IWA}(\alpha)$, and $Y^r_{IWA}(\alpha)$ are calculated by using Eqs. (18) and (19), and EKM algorithm. After all m intervals of Y_{FWA} is calculated, it can be assembled again by using *decomposition theorem* [36] as follows:

$$Y_{FWA} = \bigcup_{\alpha \in [0, h_{\min}]} Y_{FWA}(\alpha), \tag{24}$$

where $\cup$ denotes the standard fuzzy union.

Definition 4.2.4. The *Linguistic Weighted Average* (LWA), proposed in [37], is an extension of FWA for handling WA procedure in which, at least one input is modeled by IT2 FS. It should be noticed that crisp numbers, intervals, and fuzzy sets are the specific kinds of IT2 FSs, and consequently, every WA model, explained above, can be computed by using LWA. LWA is defined as

$$\tilde{Y}_{LWA} = \frac{\sum_{i=1}^{n} \tilde{X}_i \tilde{W}_i}{\sum_{i=1}^{n} \tilde{W}_i} = f(\tilde{X}_1, \ldots, \tilde{X}_n, \tilde{W}_1, \ldots, \tilde{W}_n), \tag{25}$$

where $\tilde{X}_i$ and $\tilde{W}_i$, $i = 1, \ldots, n$, are words modeled by IT2 FSs, $\tilde{Y}_{LWA}$ is also an IT2 FS which can be defined by its LMF $\underline{Y}_{LWA}$ and UMF $\bar{Y}_{LWA}$. Again, it is important to note that Eq. (25) is just a symbolic way of representing $\bar{Y}_{LWA}$. In [37], Wu and Mendel proved that computing LWA could be substituted with computing two FWAs of $\underline{Y}_{LWA}$ and $\bar{Y}_{LWA}$, and therefore, $\tilde{Y}_{LWA}$ can be computed as follows:

$$\tilde{Y}_{LWA} = \frac{1}{[\underline{Y}_{LWA}, \bar{Y}_{LWA}]}, \tag{26}$$

$$\underline{Y}_{LWA} = \frac{\sum_{i=1}^{n} \underline{X}_i \underline{W}_i}{\sum_{i=1}^{n} \underline{W}_i} = f(\underline{X}_1, \ldots, \underline{X}_n, \underline{W}_1, \ldots, \underline{W}_n), \tag{27}$$

$$\bar{Y}_{LWA} = \frac{\sum_{i=1}^{n} \bar{X}_i \bar{W}_i}{\sum_{i=1}^{n} \bar{W}_i} = f(\bar{X}_1, \ldots, \bar{X}_n, \bar{W}_1, \ldots, \bar{W}_n), \tag{28}$$

where $\underline{X}_i$ ($\bar{X}_i$) and $\underline{W}_i$ ($\bar{W}_i$), $i = 1, \ldots, n$, are the LMF (UMF) of $\tilde{X}_i$ and $\tilde{W}_i$, correspondingly. Once $\underline{Y}_{LWA}$ and $\bar{Y}_{LWA}$ are computed, $[\underline{Y}_{LWA}, \bar{Y}_{LWA}]$ constitutes the FOU ($\tilde{Y}_{LWA}$).

5. Human resource selection problem: a Per-C approach

In this section, the complete procedure for handling human resource selection problem is considered. Recall that the Per-C methodology has three steps: encoder, the CWW engine, and decoder. First, the *codebooks*, containing FOUs and names of the words used by experts, are established upon the EIA method [69] through surveys. Then, human resources are classified into two main personnel: project manager and engineer. A set of three main

competency criteria for each personnel class is determined and sub factors are explored through a literature review and survey. Next, a questionnaire survey is utilized to generate the linguistic relative importance of the criteria and sub-criteria. A data pre-processing method [79] is used to eliminate the bad data and outliers. After that, the LWA method as a CWW engine is utilized to evaluate the human resources. Finally, the average centroid ranking method and the Jaccard similarity measure are utilized to rank the results and to map them into words, correspondingly.

The human resource selection problem can be presented as follows: assume that there are set of alternatives $A = \{A_1, A_2, \ldots, \text{and } A_t\}$, which are evaluated against set of criteria C, and assume that there are m experts $D_1, D_2, \ldots, \text{and } D_m$ to determine the relative importance of criteria,. Let $C = \{C_1, C_2, C_3\}$ be the three major criteria of {technical, behavioral, contextual}, C_{ij} be the jth sub-criterion pertaining to the major criterion of C_i, $1 \le j \le n_i$, $1 \le i \le 3$, where n_i represents the number of sub-criteria for the criterion C_i, $\tilde{W}_i^k$ ($\tilde{W}_{ij}^k$) be the relative importance of criterion C_i (sub-criteria C_{ij}) provided by D_k, $1 \le k \le m$, and $\tilde{X}_i^l$ ($\tilde{X}_{ij}^l$) indicates the evaluating value of criterion C_i (sub-criteria C_{ij}) for alternative A_l, $1 \le l \le t$, then $\tilde{W}_i$ ($\tilde{W}_{ij}$) is the average relative importance of criterion C_i (sub-criteria C_{ij}), $\tilde{R}_i^l$ is the aggregated evaluation value of alternative A_l with respect to the major criterion of C_i, and $\tilde{R}^l$ is the overall performance of alternative A_l. These notations will used in the rest of this paper.

5.1. Establish codebook words

As far as we know, the only methods being developed for transforming words into FOUs are *person MF approach* [57], *interval end-points approach* [57], *interval approach (IA)* [68,70], and *enhanced interval approach (EIA)* [69]. In person MF approach, an expert needs to have a reasonable knowledge about the concepts of fuzzy set theory. On the contrary, the EIA method needs an expert just to provide interval endpoints for each word, and consequently, it can be utilized in order to avoid the mentioned difficulty. This method is able to capture the interpersonal and intrapersonal uncertainties of a word by processing interval data surveyed from a group of people. It is important to note that word survey data have to be collected from a group of experts using these words in a context of human resource selection, i.e., Chief Officers of human resource department and senior professionals within the organizations.

Table 1
Linguistic terms and their corresponding FOUs for assigning weights.

Linguistic terms	FOUs
Extremely low	EL = ((0.00,0.00,0.14,1.97;1,1),(0.00,0.00,0.05,0.66;1,1))
Very low	VL = ((0.00,1.00,1.50,2.31;1,1),(0.80,1.25,1.25,1.71;0.64,0.64))
Low	L = ((0.83,2.25,3.25,4.66;1,1),(1.84,2.75,2.75,3.66;0.64,0.64))
Medium	M = ((2.89,4.05,5.30,6.71;1,1),(4.09,4.60,4.60,5.01;0.7,0.7))
High	H = ((4.75,6.17,6.92,7.98;1,1),(5.96,6.47,6.47,6.87;0.58,0.58))
Very high	VH = ((6.75,7.92,8.92,10;1,1),(7.85,8.42,8.41,8.97;0.53,0.53))
Extremely high	EH = ((8.68,9.91,10,10;1,1),(9.61,9.97,10,10;1,1))

Two different codebooks are needed for evaluating criteria and weights. These codebooks contain nine and seven vocabulary of words, respectively. A fewer number of words are selected for weights in order to have sufficiently dissimilar words, since the human cognition capacity actually has some upper limits in making simultaneous comparison of interacted elements of words for giving reliable results. It should be noted that codebook's vocabularies have been selected based on our tentative experiments and consultations with domain experts. In light of experiments, it dawned on us that it was not practical to have more than seven words for evaluating the importance of criteria, since it made the experts indecisive in criteria importance assessment. For generating the codebooks, a group of subjects was asked to determine the end-points of an interval that appears to be associated with each word. Then, the collected intervals were used to establish a FOU for each word by using EIA method. For more details on how data are processed and mapped to IT2 FSs, see [68,69]. The word names and associated FOUs are listed in Tables 1 and 2, and shown in Figs. 4 and 5.

5.2. Develop competency criteria hierarchy

Competency is a cluster of related knowledge, attitudes, skills, and personal characteristics that [80]:

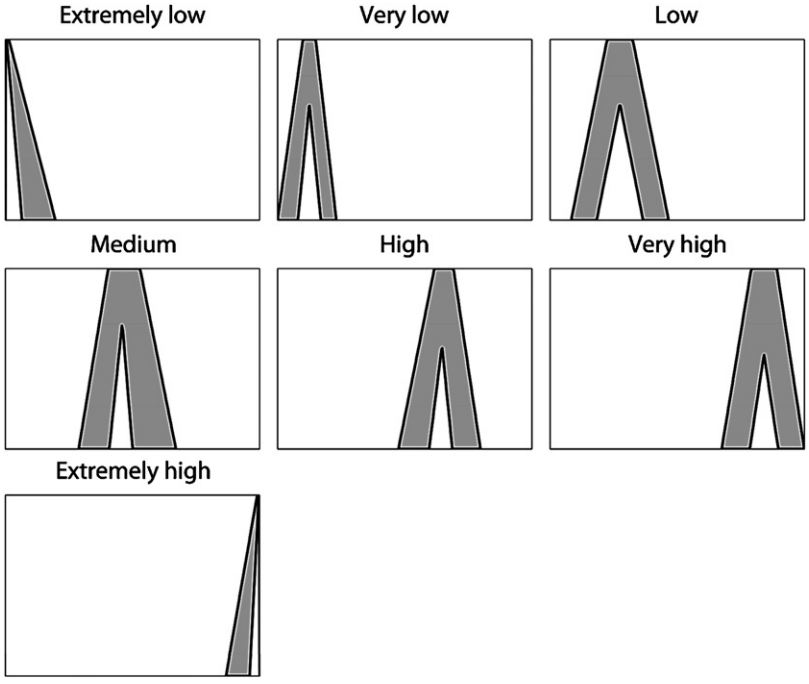


Fig. 4. FOUs of the linguistic terms of weights.

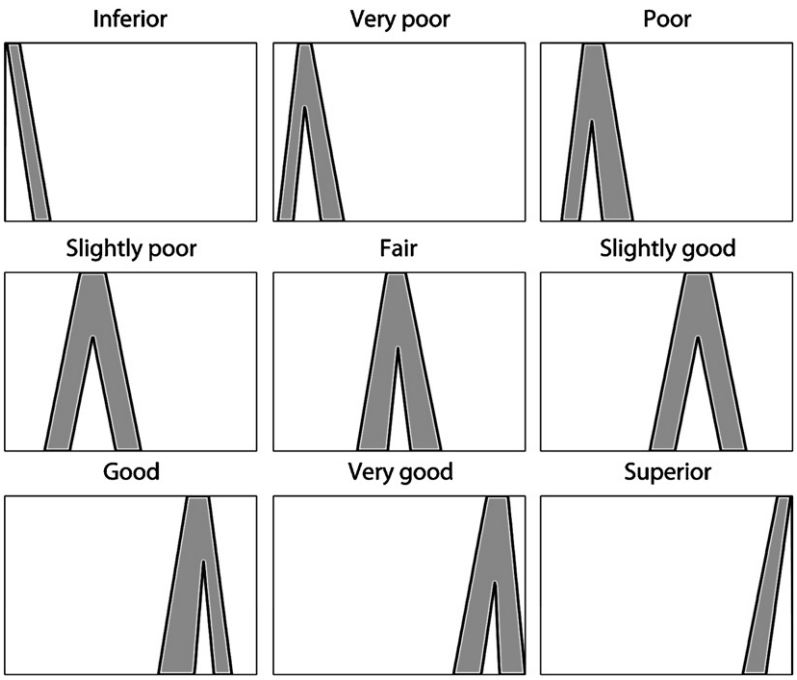


Fig. 5. FOUs of the linguistic terms of criteria.

- Affects a major part of one's job
- Correlates with performance on the job
- Can be measured against well-accepted standards
- Can be improved via training and development
- Can be broken down into dimensions of competence

In order to determine competency development framework, main personnel of construction companies according to UDL/ETA [81] are classified as follows: project manager and engineer.

5.2.1. Main personnel occupations

To describe main occupations, and clarify their tasks and job zones, a brief description of 'main personnel' is mentioned in the following: a project manager is a person accountable for accomplishing the stated project objectives. Fundamental project management responsibilities include creating clear and attainable project objectives, building the project requirements, and managing the triple constraint for projects, which are cost, time, and quality [1]. An engineer is a person who has the profession in which a knowledge of the mathematical and physical sciences, experience, and practice are applied with a matter of judgment in order to develop procedures to utilize, economically, materials and forces of nature in creating, improving, and protecting the environment, and in providing structures for use of the progressive well-being of humanity [82].

Table 2
Linguistic terms and their corresponding FOUs for evaluating criteria.

Linguistic terms	FOUs
Inferior	I = ((0,0,0.59,1.81;1,1),(0,0,0.09,1.16;1,1))
Very poor	VP = ((0.18,1,1.50,2.80;1,1),(0.79,1.25,1.25,1.90;0.65,0.65))
Poor	P = ((0.83,1.70,2.50,3.66;1,1),(1.54,2.04,2.04,2.45;0.56,0.56))
Slightly poor	SP = ((1.58,3.00,4.00,5.41;1,1),(2.58,3.5,3.50,4.41;0.65,0.65))
Fair	F = ((3.33,4.50,5.25,6.66;1,1),(4.54,4.95,4.95,5.45;0.58,0.58))
Slightly good	SG = ((4.33,5.75,6.75,8.16;1,1),(5.33,6.25,6.25,7.16;0.65,0.65))
Good	G = ((6.10,7.25,8.10,9.01;1,1),(7.53,7.89,7.89,8.31;0.64,0.64))
Very good	VG = ((7.15,8.48,9.32,10;1,1),(8.25,8.81,8.81,8.97;0.53,0.53))
Superior	S = ((8.03,9.41,10,10;1,1),(8.94,9.92,10,10;1,1))

5.2.2. Hierarchical competency criteria of personnel

Competency models are highly useful tools to make sure that human resource systems facilitate and support company's strategic objectives. It increases the likelihood of placing the right people into the right jobs [82]. Because of inherent differences between the two main classes that are mentioned previously, their competency models are accordingly different. Therefore, two different competency hierarchies are established for project manager and engineer. In order to determine the competency criteria hierarchy of construction personnel, three main factors of technical, behavioral and contextual competency and their sub-competency factors were identified through an extensive literature review and a series of interviews. For interviewing, a questionnaire was administered to top ten contractors selected from the Grade 1 building contractors in Tehran, Iran.

Project manager hierarchical competency criteria: Project manager's competencies can be described as three separate dimensions of technical, behavioral and contextual competencies. For each dimension, according to International Project Management Association [83], hierarchical structure of competency criteria for a project manager is identified in Table 3.

Engineer hierarchical competency criteria: Engineer competencies are described as three dimensions of technical, behavioral and contextual competencies. According to UDL/ETA [81], ASCE [82], EA [84] and a series of interviews, hierarchical structure of competency criteria for an engineer is identified in Table 4.

5.3. Determine criteria weights

The relative importance of each criterion can be determined in two ways: pairwise comparison, and direct assignment, which the direct assignment is utilized in this paper. For each main personnel class, a structured questionnaire was developed to gather expert opinions. The questionnaire was requested to be completed by a Chief Officer (CO) of human resource department or a senior professional within the organization of the 10 top contractors. In the main body of the questionnaire, respondents were invited to evaluate the relative importance of competencies and sub-competency

Table 3
Histogram of survey responses for competency criteria of project manager.

Project manager competencies		Weights						
		EL	VL	L	M	H	VH	EH
C_1	**Technical competencies**	**0**	**0**	**1**	**2**	**2**	**4**	**1**
C_{11}	Project management success	0	2	2	3	2	1	0
C_{12}	Interested parties	0	0	2	3	1	2	2
C_{13}	Project requirements	0	2	3	2	1	1	1
C_{14}	Risk & opportunity	0	0	2	4	3	1	0
C_{15}	Quality	1	3	4	1	1	0	0
C_{16}	Project organization	2	4	2	1	1	0	0
C_{17}	Teamwork	0	0	1	2	2	2	3
C_{18}	Problem resolution	0	1	2	4	2	1	0
C_{19}	Project structures	4	3	2	1	0	0	0
C_{110}	Scope & deliverables	2	3	2	2	1	0	0
C_{111}	Time & project phases	0	0	0	2	2	3	3
C_{112}	Resources	0	1	2	2	2	2	1
C_{113}	Cost & finance	0	0	0	2	1	5	2
C_{114}	Procurement & contract	0	1	2	3	2	2	0
C_{115}	Changes	1	2	3	2	2	0	0
C_{116}	Control & reports	0	0	1	2	4	2	1
C_{117}	Information & documentation	0	0	2	1	2	4	1
C_{118}	Communication	0	1	2	2	3	1	1
C_{119}	Start-up	1	2	3	3	1	0	0
C_{120}	Close-out	1	0	1	3	2	2	1
C_2	**Behavioral competencies**	**1**	**1**	**2**	**3**	**2**	**1**	**0**
C_{21}	Leadership	0	0	0	1	1	3	5
C_{22}	Engagement & motivation	0	0	1	0	2	5	2
C_{23}	Self-control	0	2	3	4	1	0	0
C_{24}	Assertiveness	0	1	1	1	2	3	2
C_{25}	Relaxation	2	3	1	2	1	1	0
C_{26}	Openness	0	0	1	3	4	1	1
C_{27}	Creativity	0	0	2	3	2	2	1
C_{28}	Results orientation	4	3	2	1	0	0	0
C_{29}	Efficiency	1	2	5	0	1	1	0
C_{210}	Consultation	0	0	2	3	2	2	1
C_{211}	Negotiation	2	3	3	2	0	0	0
C_{212}	Conflict & crisis	0	0	1	2	3	3	1
C_{213}	Reliability	0	0	1	2	2	3	2
C_{214}	Values appreciation	1	0	2	2	3	1	1
C_{215}	Ethics	0	0	1	2	2	2	3
C_3	**Contextual competencies**	**2**	**2**	**3**	**2**	**1**	**0**	**0**
C_{31}	Project orientation	0	0	2	4	3	2	1
C_{32}	Program orientation	5	2	2	1	0	0	0
C_{33}	Portfolio orientation	0	0	0	1	2	4	3
C_{34}	PPP implementation	2	4	3	1	0	0	0
C_{35}	Permanent organization	0	0	1	1	2	3	3
C_{36}	Business	4	3	2	1	0	0	0
C_{37}	Systems, products & technology	1	2	3	2	1	1	0
C_{38}	Personnel management	0	0	0	1	2	2	5
C_{39}	Health, safety & environment	0	0	1	1	4	3	1
C_{310}	Finance	2	2	3	1	1	1	0
C_{311}	Legal	0	0	1	1	3	3	2

Table 4
Histogram of survey responses for competency criteria of engineer.

Engineer competencies		Number of Scorings						
		EL	VL	L	M	H	VH	EH
C_1	**Technical competencies**	**0**	**0**	**0**	**1**	**2**	**5**	**2**
C_{11}	Engineering practice	0	0	0	1	3	2	4
C_{12}	Engineering planning	0	1	1	3	2	2	1
C_{13}	Engineering design	0	0	0	1	1	4	4
C_{14}	Engineering operation	0	0	1	4	2	3	0
C_{15}	Determine systems	1	0	0	3	2	2	2
C_{16}	Investigation and reporting	1	1	5	1	2	0	0
C_{17}	Research and development	1	1	3	3	1	1	0
C_{18}	Defines resources	0	0	0	2	2	3	3
C_{19}	Estimate materials	0	0	0	1	3	4	2
C_{110}	Changes	1	2	3	2	1	1	0
C_{111}	Technical development	2	2	3	2	1	0	0
C_{112}	Technical promotion	4	3	2	1	0	0	0
C_2	**Behavioral competencies**	**0**	**1**	**3**	**4**	**2**	**0**	**0**
C_{21}	Cooperation	0	0	1	2	1	4	2
C_{22}	Commitment	0	0	1	1	3	3	2
C_{23}	Independence	0	1	2	3	1	2	1
C_{24}	Efficiency	0	1	1	2	2	4	0
C_{25}	Attention to detail	0	1	4	2	1	1	1
C_{26}	Coaching	5	4	1	0	0	0	0
C_{27}	Communication skills	0	0	1	2	4	2	1
C_{28}	Creativity	0	0	0	1	2	3	4
C_{29}	Initiative	0	0	1	3	1	3	2
C_{210}	Judgment	0	2	2	2	3	1	0
C_{211}	Teamwork	0	0	1	1	2	2	4
C_{212}	Values diversity	0	1	1	3	3	1	0
C_{213}	Ethics	0	0	1	3	2	4	0
C_3	**Contextual competencies**	**0**	**1**	**2**	**3**	**2**	**1**	**1**
C_{31}	Project orientation	0	0	2	3	3	1	1
C_{32}	Program orientation	4	2	2	2	0	0	0
C_{33}	Portfolio orientation	5	3	1	1	0	0	0
C_{34}	PPP implementation	0	1	3	2	3	1	0
C_{35}	Self-management	0	0	1	1	2	3	3
C_{36}	Engineering project management	0	0	1	2	2	2	3
C_{37}	Environmental management	0	1	2	1	2	3	1
C_{38}	Systems & products	5	2	2	1	0	0	0
C_{39}	Personnel management	1	1	2	2	3	1	0
C_{310}	Health, security & safety	0	0	0	2	2	2	4
C_{311}	Legal	1	1	2	2	3	1	0

factors by using linguistic terms defined in Table 1. The histogram of survey responses are listed in Tables 3 and 4. After applying the data pre-processing steps described in [79], the average weight for each criteria and sub-criteria is determined using Eqs. (12) and (13) as follows:

$$\tilde{W}_i = \frac{(\tilde{W}_i^1 \oplus \tilde{W}_i^2 \oplus \cdots \oplus \tilde{W}_i^m)}{m}, \tag{29}$$

$$\tilde{W}_{ij} = \frac{(\tilde{W}_{ij}^1 \oplus \tilde{W}_{ij}^2 \oplus \cdots \oplus \tilde{W}_{ij}^m)}{m}, \tag{30}$$

where $\tilde{W}_i^k$ ($\tilde{W}_{ij}^k$) is the relative importance of criterion C_i (sub-criteria C_{ij}) provided by D_k, m is the number of responders, $\tilde{W}_i$ ($\tilde{W}_{ij}$) is the average relative importance of criterion C_i (sub-criteria C_{ij}), $1 \le i \le 3$, and $1 \le j \le n_i$. It is assumed that the responders are equally important. For the sake of brevity, the averaged weights are only given for the competencies of project manager, as listed in Table 5. In addition, the averaged weights of major criteria for project manager are depicted in Fig. 6.

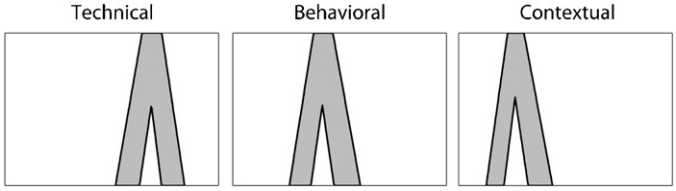


Fig. 6. FOUs of the averaged weights of major criteria for project manger.

5.4. CWW engine

Since all evaluations and weights are words, LWA is exploited as a CWW engine to aggregate the criteria and sub-criteria values and, hence, to obtain the overall evaluation of each personnel. During the aggregation process, each of the major criteria, i.e., technical, behavioral, and contextual, has an LWA computed for it, and then these three LWAs are aggregated by using another LWA to obtain the overall evaluation of each personnel. More specifically

$$\tilde{R}_i^l = \frac{\sum_{j=1}^{n_i} \tilde{W}_{ij} \times \tilde{X}_{ij}^l}{\sum_{j=1}^{n_i} \tilde{W}_{ij}}, \tag{31}$$

$$\tilde{R}^l = \frac{\tilde{W}_1 \times \tilde{R}_1^l + \tilde{W}_2 \times \tilde{R}_2^l + \tilde{W}_3 \times \tilde{R}_3^l}{\tilde{W}_1 + \tilde{W}_2 + \tilde{W}_3}, \tag{32}$$

in which, $\tilde{R}_i^l$ is the aggregated value of the alternative A_l with respect to the major criterion of C_i, $1 \le i \le 3$, and $\tilde{R}^l$ is the overall

performance of the alternative A_l. It should be noted that all inputs in Eqs. (31) and (32) are words represented by IT2 FSs, and the results $\tilde{R}_i^l$ and $\tilde{R}^l$ are also IT2 FSs calculated using Eqs. (25)–(29).

5.5. Decoder

There have been many methods proposed for the decoding problem, which is the process of mapping the results represented by IT2 FSs into recommendations, rankings, or classes [34]. In this paper, we use the average centroid ranking method [34] for ranking IT2 FSs based on their center of centroids, and Jaccard similarity measure [34] for measuring the degree of similarity between the result's IT2 FSs and the codebook to map them into words. For scoring the results, the $Rank(\tilde{R}^l)$ of each IT2 FS $\tilde{R}^l$ can be calculated by Eq. (10), where $1 \le l \le t$, and for mapping the results into recommendations, the degree of similarity between $\tilde{R}^l$ and each of target output terms can be calculated by Eq. (11) in order to decode the results from IT2 FSs into linguistic terms. In the former, the larger the value of $Rank(\tilde{R}^l)$, the higher the overall performance of the person; and in the latter, the linguistic term from the target output terms with the largest degree of similarity with $\tilde{R}^l$ is equal to the overall performance value of A_l.

Table 5
The averaged weights for project manager competencies.

Project manager competencies	Final IT2 FS of weights $((a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U; H_{i1}^U, H_{i2}^U), (a_{i1}^L, a_{i2}^L, a_{i3}^L, a_{i4}^L; H_{i1}^L, H_{i2}^L))$
C_1	**((5.18,6.43,7.36,8.40;1,1),(6.30,6.85,6.85,7.33;0.53,0.53))**
C_{11}	((2.66,3.89,4.82,6.00;1,1),(3.73,4.32,4.32,4.85;0.53,0.53))
C_{12}	((4.60,5.85,6.72,7.74;1,1),(5.68,6.25,6.26,6.72,0.53,0.53))
C_{13}	((2.85,4.08,4.92,6.00;1,1),(3.87,4.48,4.48,5.03,0.53,0.53))
C_{14}	((3.42,4.71,5.74,7.01;1,1),(4.58,5.17,5.17,5.70,0.53,0.53))
C_{15}	((0.69,1.78,2.55,3.81;1,1),(1.54,2.15,2.16,2.83,0.65,0.65))
C_{16}	((0.51,1.39,2.01,3.25;1,1),(1.22,1.68,1.69,2.28,0.65,0.65))
C_{17}	((5.57,6.83,7.55,8.40;1,1),(6.65,7.16,7.17,7.54,0.53,0.53))
C_{18}	((2.95,4.20,5.20,6.44;1,1),(4.06,4.65,4.65,5.18,0.53,0.53))
C_{19}	((0.19,0.83,1.28,2.68;1,1),(0.67,1.03,1.05,1.68,0.65,0.65))
C_{110}	((1.22,2.18,2.88,4.16;1,1),(2.02,2.49,2.50,3.07,0.58,0.58))
C_{111}	((6.16,7.39,8.12,8.94;1,1),(7.25,7.73,7.74,8.07,0.53,0.53))
C_{112}	((3.91,5.17,6.03,7.10;1,1),(4.99,5.57,5.57,6.08,0.53,0.53))
C_{113}	((6.17,7.37,8.21,9.14;1,1),(7.27,7.77,7.78,8.18,0.53,0.53))
C_{114}	((3.34,4.58,5.56,6.77;1,1),(4.44,5.03,5.03,5.58,0.53,0.53))
C_{115}	((1.78,2.92,3.73,5.00;1,1),(2.72,3.29,3.29,3.88,0.58,0.58))
C_{116}	((4.78,6.08,6.94,8.00;1,1),(5.92,6.46,6.47,6.91,0.53,0.53))
C_{117}	((4.98,6.25,7.13,8.20;1,1),(6.07,6.67,6.67,7.20,0.53,0.53))
C_{118}	((3.71,4.99,5.83,6.90;1,1),(4.80,5.37,5.38,5.87,0.53,0.53))
C_{119}	((1.59,2.71,3.57,4.87;1,1),(2.53,3.10,3.11,3.70,0.58,0.58))
C_{120}	((4.58,5.83,6.76,7.86;1,1),(5.71,6.25,6.26,6.71,0.53,0.53))
C_2	**((2.66,3.79,4.67,6.97;1,1),(3.65,4.19,4.19,4.74;0.53,0.53))**
C_{21}	((7.13,8.35,8.90,9.47;1,1),(8.17,8.62,8.63,8.88,0.53,0.53))
C_{22}	((6.74,7.97,8.71,9.55;1,1),(7.83,8.33,8.34,8.74,0.53,0.53))
C_{23}	((1.88,3.11,4.09,5.34;1,1),(2.94,3.56,3.56,4.13,0.58,0.58))
C_{24}	((5.09,6.32,7.06,7.96;1,1),(6.14,6.67,6.68,7.11,0.53,0.53))
C_{25}	((1.81,2.74,3.45,4.69;1,1),(2.62,3.06,3.07,3.60,0.53,0.53))
C_{26}	((3.92,5.22,6.19,7.41;1,1),(5.09,5.65,5.65,6.13,0.53,0.53))
C_{27}	((4.20,5.47,6.41,7.54;1,1),(5.32,5.90,5.91,6.41,0.53,0.53))
C_{28}	((0.19,0.83,1.28,2.68;1,1),(0.67,1.03,1.05,1.68,0.65,0.65))
C_{29}	((0.52,1.66,2.42,3.74;1,1),(1.35,2.03,2.04,2.80,0.65,0.65))
C_{210}	((4.20,5.47,6.41,7.54;1,1),(5.32,5.90,5.91,6.41,0.53,0.53))
C_{211}	((0.83,1.79,2.51,3.83;1,1),(1.61,2.12,2.13,2.75,0.65,0.65))
C_{212}	((4.98,6.25,7.14,8.20;1,1),(6.11,6.66,6.66,7.12,0.53,0.53))
C_{213}	((5.37,6.63,7.44,8.40;1,1),(6.47,7.01,7.01,7.44,0.53,0.53))
C_{214}	((4.13,5.44,6.31,7.41;1,1),(5.24,5.83,5.84,6.33,0.53,0.53))
C_{215}	((5.57,6.83,7.55,8.40;1,1),(6.65,7.16,7.17,7.54,0.53,0.53))
C_3	**((1.30,2.30,3.05,4.40;1,1),(2.13,2.64,2.65,3.26;0.57,0.57))**
C_{31}	((3.73,5.00,6.03,7.28;1,1),(4.88,5.47,5.47,6.00,0.53,0.53))
C_{32}	((0.46,1.06,1.55,3.05;1,1),(0.94,1.26,1.29,1.91,0.65,0.65))
C_{33}	((6.55,7.78,8.48,9.27;1,1),(7.63,8.11,8.12,8.47,0.53,0.53))
C_{34}	((0.54,1.48,2.13,3.39;1,1),(1.28,1.79,1.80,2.42,0.65,0.65))
C_{35}	((5.95,7.21,7.91,8.73;1,1),(7.03,7.55,7.55,7.94,0.53,0.53))
C_{36}	((0.46,1.16,1.69,3.09;1,1),(1.02,1.39,1.41,2.01,0.65,0.65))
C_{37}	((1.98,3.09,3.93,5.20;1,1),(2.91,3.48,3.49,4.09,0.53,0.53))
C_{38}	((6.93,8.18,8.70,9.27;1,1),(7.98,8.42,8.44,8.67,0.53,0.53))
C_{39}	((5.65,6.93,7.75,8.74;1,1),(6.79,7.30,7.30,7.72,0.53,0.53))
C_{310}	((1.69,2.69,3.42,4.72;1,1),(2.50,3.02,3.03,3.66,0.53,0.53))
C_{311}	((6.09,7.35,8.09,8.96;1,1),(7.20,7.69,7.70,8.06,0.53,0.53))

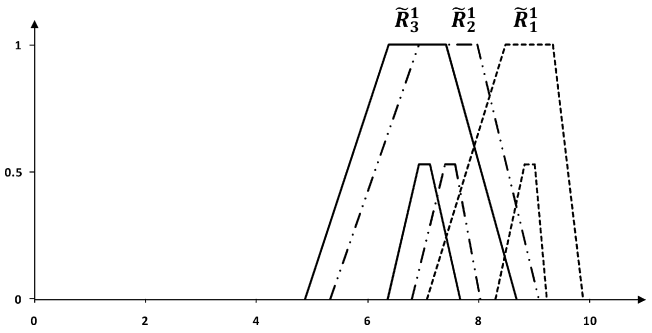


Fig. 7. Aggregation results for major criteria of alternative A_1.

6. Empirical example

The purpose of the empirical application is to illustrate the use of the suggested procedure. The experiment was basically setup upon a real life decision. The company for conducting the experiment was nominated from the ten previously mentioned Iranian construction companies which the data of preceding sections of this paper had been collected through them. The Chief Officer (CO) of human resource department of the nominated company decided to examine the proposed procedure in evaluation of the already employed middle and high-level project managers. This course of action was so beneficial since it made the experiment results examinable due to the comparability of the results with the existing performance records of the project managers to be investigated and the intuitive preferences of the CO and the other contributor managers. The experiment was conducted according to steps described in the previous sections with using the linguistic terms of Table 2 against the mentioned hierarchical competency-based criteria of project manager, listed in Table 3, by the CO. For the sake of better tractability, three investigated manager $A = \{A_1, A_2, A_3\}$ with easily discernable results are presented in this section. The assigned linguistic terms for each of three alternatives in each criterion by the CO are shown in Table 6.

The results of the proposed methodology for each major criteria of the alternatives based on Eq. (31) are depicted in Figs. 7–9. Based on Eq. (32), the overall performance of each alternative is obtained. The overall results are depicted in Fig. 10, and shown as follows:

$$\tilde{R}^1 = ((5.70, 7.53, 8.62, 9.60; 1, 1), (7.36, 8.03, 8.22, 8.64; 0.53, 0.53)),$$

$$\tilde{R}^2 = ((3.21, 5.00, 6.23, 7.95; 1, 1), (4.77, 5.56, 5.78, 6.55; 0.53, 0.53)),$$

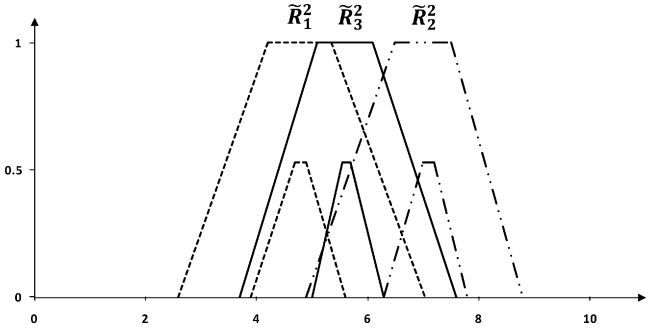


Fig. 8. Aggregation results for major criteria of alternative A_2.

Table 6
Scores of selected project managers in criteria by linguistic values.

Criteria	Participants		
	A_1	A_2	A_3
C_1			
C_{11}	VG	SG	SG
C_{12}	S	SP	SP
C_{13}	VG	F	P
C_{14}	G	SG	F
C_{15}	VG	P	SP
C_{16}	S	SP	SG
C_{17}	G	G	P
C_{18}	VG	SG	F
C_{19}	VG	SP	P
C_{110}	S	P	SP
C_{111}	S	P	SG
C_{112}	VG	SG	SP
C_{113}	VG	F	P
C_{114}	S	SP	P
C_{115}	VG	SG	SP
C_{116}	S	SP	SG
C_{117}	VG	SG	F
C_{118}	G	SP	SG
C_{119}	VG	F	F
C_{120}	VG	F	F
C_2			
C_{21}	S	SG	SG
C_{22}	VG	G	F
C_{23}	F	F	SP
C_{24}	G	G	F
C_{25}	G	VG	F
C_{26}	VG	G	SG
C_{27}	SG	SG	P
C_{28}	G	F	SG
C_{29}	VG	G	SP
C_{210}	F	VG	SP
C_{211}	VG	G	F
C_{212}	SG	SG	F
C_{213}	F	SG	G
C_{214}	VG	G	F
C_{215}	G	SG	SP
C_3			
C_{31}	G	SG	SP
C_{32}	G	F	P
C_{33}	SG	F	P
C_{34}	G	SP	VP
C_{35}	SG	F	P
C_{36}	F	SG	SP
C_{37}	VG	F	P
C_{38}	G	F	P
C_{39}	F	SG	SP
C_{310}	G	F	P
C_{311}	G	G	F

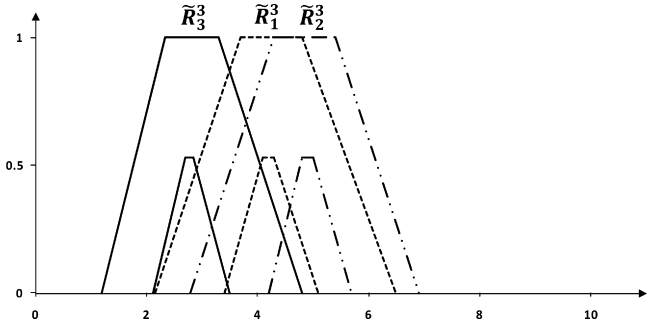


Fig. 9. Aggregation results for major criteria of alternative A_3.

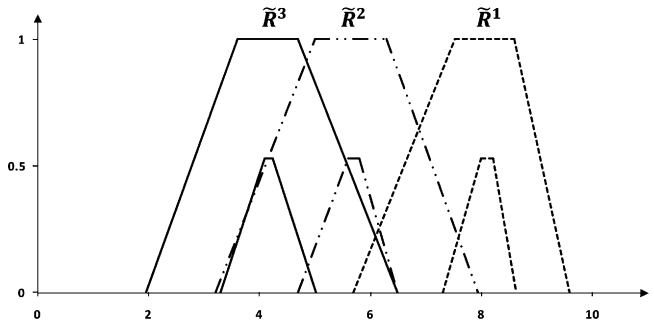


Fig. 10. Overall results of the three alternatives.

$$\tilde{R}^3 = ((1.95, 3.55, 4.73, 6.53; 1, 1), (3.30, 4.06, 4.26, 5.03; 0.53, 0.53)).$$

If the ranking values of the alternatives are calculated based on Eq. (10), the final ranking values are obtained as follows:

$$Rank(\tilde{R}^1) = 7.91 > Rank(\tilde{R}^2) = 5.62 > Rank(\tilde{R}^3) = 4.19,$$

which are totally in accordance with the intuitive preference of the CO. This is an indication of the usefulness of this approach. In addition, for decoding the overall performance values into linguistic terms, based on Eq. (11), the Jaccard similarity measure is used to calculate the degree of similarity between each overall performance value $\tilde{R}^l$ and each linguistic term shown in Table 2. The degree of similarity between $\tilde{R}^1$ and each of the linguistic terms of Table 2 are

$$s_J(\tilde{R}^1, I) = 0, \quad s_J(\tilde{R}^1, VP) = 0, \quad s_J(\tilde{R}^1, P) = 0, \quad s_J(\tilde{R}^1, SP) = 0,$$
$$s_J(\tilde{R}^1, F) = 0.024, \quad s_J(\tilde{R}^1, SG) = 0.181, \quad s_J(\tilde{R}^1, G) = 0.691,$$
$$s_J(\tilde{R}^1, VG) = 0.377, \quad s_J(\tilde{R}^1, S) = 0127.$$

In the same way, we can calculate the degree of similarity of $\tilde{R}^2$ and $\tilde{R}^3$ with each of the linguistic terms represented in Table 2. Based on the largest degree of similarity among the calculated results, the overall performance value $\tilde{R}_1$ is mapped to "Good", $\tilde{R}_2$ is mapped to "Slightly good", and $\tilde{R}_3$ is mapped to "Slightly poor". It is important to note that human resources, generally, are filed in resource pool according to their overall competency levels. From a practical point of view, there is no fundamental difference between the personnel classified in each competency level in the resource pool. This resource pool is then employed for the real assignment of staff to various roles. Therefore, mapping of overall performance IT2 FSs into linguistic terms serves a basis for the formation of resource pool.

7. Conclusions

The aim of this paper was to develop the Perceptual Computer model, as a specific architecture and as an instantiation of Zadeh's CWW paradigm, for competency based selection of personnel in construction companies. Competency-based evaluation and selection is performed for each class of jobs and careers and serves as a link between different steps of human resource management. Classical job classification and evaluation processes take position roles and responsibilities into account for the selection problem. By contrast, in competency-based selection procedure, overall competencies of personnel are evaluated by the competency framework established for each specific job class. The latter, indeed, leads to the fair evaluation of personnel.

In the proposed methodology, all the inputs to the personnel selection model are words, represented by IT2 FSs, to make up for some shortages of previous models and to ease the decision making process when the experts can only provide qualitative information based on their subjective perceptions. The specificity of this problem stemmed from its vague and imprecise information and judgments, i.e., candidate evaluations are under uncertainty, their competencies cannot be evaluated correctly without considering the related uncertainties, and linguistic descriptors are usually used by experts in this area. To tackle these issues, we exploited the remarkable vagueness modeling capability of interval type-2 fuzzy sets in order to address the uncertainties associated with words used normally by experts. It should be noted that interval type-2 fuzzy representation of a word is the least realistic descriptor concerning the word nature, since it is an obvious contradiction to mold an uncertain concept with a certain one. Other reduced representations, such as type-1 fuzzy sets, are just rough approximations. By modeling the words with IT2 FSs, no pre-processing and reduction approaches are utilized, and as a result, all accompanying uncertainties flow all through the calculation processes.

The distinguishing feature of using Per-C architecture and the LWA method in this problem is that all the uncertainties about the words, sub criteria scores and criteria weights can flow and be aggregated all through the calculations and be reflected in the overall results, and consequently, no information is lost. Besides, all word's FOUs are established directly, without any prior assumptions, upon the interval endpoint data collected from a group of experts and as a result, are realistic representations of the linguistic terms. In addition, the IT2 FS result of performance evaluation contains much more information than just a single ranking number, since the UMF and LMF of each result represents the upper bound and lower bound of possibility associated with each grade. In other words, each individual is actually evaluated by the FOU, which contain uncertainty information in addition to ranking and similarity information. This advantage can be effortlessly seen in Figs. 7–10. The complying of the empirical experiment results with the existing performance records and the intuitive preferences of the experts also showed that the proposed approach has practical implementations for real-world problems. This approach provides the experts with a useful tool to handle the problem in more flexible and intelligent manner.

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