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A Type-2 Fuzzy Based System for Handling the Uncertainties in Group Decisions for Ranking Job Applicants within Human Resources Systems

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***Abstract*—Ranking applicants for a given job is one of the most important processes for Human Resources (HR) systems. The ranking of job applicants involves two main processes which are the *specification of the requirements criteria* for a given job (experience, skills, etc) and the *matching* between the applicants' profiles and the job requirements. There is currently a strong move towards automating these two processes to generate an applicants' ranking system that gives consistent and fair results. However there is a high level of uncertainty involved in these two processes as they involve the input of several experts. These experts will have different opinions, expectations the interpretations for the requirements specification as well as for the applicants matching and ranking. This paper presents a novel approach for ranking job applicants by employing type-2 fuzzy sets for handling the uncertainties in group decisions in a panel of experts. Hence the presented system will enable automating the processes of requirements specification and applicants matching/ranking. We have performed real world experiments in the care domain where our system handled the uncertainties and produced ranking decisions that were consistent with those of the human experts. To the authors' knowledge, this will be the first type-2 based commercial software system.**

I. Introduction

The process of ranking and short-listing applicants for particular job roles in an organisation is based on matching the applicant's profile and Curriculum Vitae (CV) against the requirements criteria (experience, skills, knowledge and qualifications, etc) the post holder needs in order to perform the duties of the job [6]. This process is usually conducted by recruitment experts [6]. One of the problems within this process is that there is no systematic and consistent way for specifying the requirements criteria and the matching/ranking policy. Within the UK, USA and the European Union, it is now a legal requirement for employers to provide clear reasons for short-listing or rejecting job applicants based on identifying how much of the job requirements criteria the applicants satisfy. Hence, accurately specifying the job requirements criteria (which is usually referred to as the ***person specification***) is of vital importance as it provides: a comprehensive break down of the characteristics on which to rank and short list suitable applicants for the job post. In addition, these requirements criteria could be used to provide a justification for the selection decisions.

The task of formulating a new person specification (job requirement) for a given job role is the responsibility of the organisation Human Resources (HR) manager. This usually involves a group decision making process to derive a collective opinion from a selection panel of individuals who have expertise related to the occupation domain associated with the job role. Each expert's opinions and preferences for the job requirements can vary based on their roles in the organisation, knowledge and experience pertaining to the occupation domain. Each expert can also consider certain characteristics more or less important than others. The variations in the opinions of experts cause high level of uncertainties when specifying the job requirements. Conventional attempts at addressing these uncertainties are through meetings and discussion sessions which can be both time consuming and difficult to coordinate for different departments and divisions of the organisation. The varying opinions of each expert can make it difficult to achieve an agreement or consensus among the group. In addition, the final decision may not always reflect the opinions of all the experts in a consistent and objective way. The difficulty increases for big multinational organisations which might need to develop an international advert for a given job role.

There are several approaches within the literature that use fuzzy logic for modelling group decision making process [2], [3], [4]. These models deal with decision situations in which a set of experts have to choose the best alternative or alternatives from a feasible set of alternatives. The different processes which have been focused on are: the consensus process and selection process [1]. The former consists of obtaining the highest consensus (agreement) among experts to obtain a state where the opinions of the different experts are as close as possible to one another [1]. The latter process consists of obtaining the final solution to the problem from the opinions expressed by the experts in the consensus process [1]. Recent work in [2] presented an automated system that handles incomplete and imprecise knowledge about experts' preferences using incomplete fuzzy preference relations. The consensus producing mechanism is an iterative process with several consensus rounds, in which the experts accept to change their preferences following advice generated by the system in order to obtain a solution with a

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high degree of consensus between the experts [2]. In these systems there is also much focus throughout the process on maintaining consistency of information and avoiding contradiction between the opinions and preferences of different experts [3].

The approaches outlined above are based on type-1 fuzzy logic approaches for achieving a group consensus on a set of known solutions. However, these approaches do not aim to model and handle the uncertainties involved within the group decision process.

Type-2 fuzzy systems could be used to handle the uncertainties in the group decision making process as they can model the uncertainties between expert preferences using type-2 fuzzy sets. A type-2 fuzzy set is characterized by a fuzzy Membership Function (MF), i.e. the membership value (or membership grade) for each element of this set set in [0,1], unlike a type-1 fuzzy set where the m grade is a crisp number in [0,1] [8]. The MFs of ty sets are three dimensional and include a Footprint Of Uncertainty (FOU). Hence, type-2 fuzzy sets provide additional degrees of freedom that can make it possible to model the group uncertainties between the varying opinions and preferences of experts. The type-2 fuzzy sets can model the requirements of a person specification that's reflective of all the experts' opinions and can then be used to accurately rank applicants for the job role.

In this paper, we present a novel technique for automating the process ranking applicant CVs using a type-2 fuzzy approach for handling the group decisions in a selection panel of experts. The system creates a person specification that captures the job role requirements preferences from the group of experts in a consistent and objective way by modelling the uncertainties between the experts' preferences using type-2 fuzzy sets. A scoring method is proposed that scores applicant's CVs based on how well they match the requirements preferences of each expert. The scores are mapped to the type-2 fuzzy sets to determine a ranking for the CVs. We will present real world experiments in the care domain where our system handled the uncertainties and produced ranking decisions that are consistent with those of the human experts. Our ranking technique is also completely transparent and provides human interpretable reasons for all ranking decisions.

In Section II, we will briefly describe the type-2 fuzzy sets. Section III will describe our type-2 fuzzy group decision modelling and CV ranking technique. In Section IV, we will present the experiments and results. Finally conclusions are presented in Section V.

II. The Type-2 Fuzzy Sets

Type-2 fuzzy sets are able to model the uncertainties because their MFs are themselves fuzzy [8]. Imagine blurring the type-1 MF (drawn in dotted line) that is depicted in Fig. 1 by shifting the points on the triangle either to the left or to the right and not necessarily by the same amounts. Then, at a specific value of x, say x', there is no longer a single value for the MF (u'); instead, the MF takes on values wherever the vertical line intersects the blurred area shaded in grey [8]. Those values need not all be weighted the same; hence, we can assign an amplitude distribution to all of those points. Doing this for all $x \in X$, we create a three-dimensional MF—a type-2 MF—that characterizes a type-2 fuzzy set [8]. When this third dimension amplitude distribution is equal to $1 \ \forall u \in J_x \subseteq [0,1]$, and, if this is true for $\forall x \in X$, we have the case of an interval type-2 MF which characterizes the interval type-2 fuzzy sets [7]. The shaded area in grey in Fig. 1 is termed the FOU which is bounded by two type-1 MFs which are the upper MF ($\overline{\mu}_{\tilde{A}}(x)$) and the lower MF ($\underline{\mu}_{\tilde{A}}(x)$) [7]. An interval type-2 fuzzy set $\tilde{A}$ is written as:

$$\tilde{A} = \int \left[\int 1/u \right] / x \qquad (1)$$

FOU provide additional degrees of freedom that can make it possible to directly model and handle the uncertainties [7], [8]. These additional degrees of freedom enable type-2 fuzzy sets to handle the uncertainties that can arise in group decision making to enable it to better model the collective group opinion.

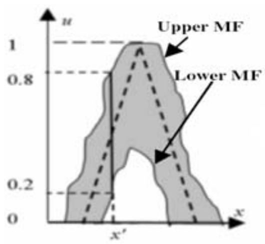

Fig. 1. A type-2 MF formed by blurring the type-1 MF drawn in dashed line.

III. The Type-2 Fuzzy Group Decision Modelling and CV Ranking Technique

Each job role is defined within an occupation domain that is associated with a set of characteristics. These characteristics comprise of the skills, qualifications, knowledge and competencies from which a person specification for the job role would be created. The occupation characteristics may be derived from an occupation database, employment taxonomy or could be specific to the job areas defined within an organisation. Our type-2 fuzzy group decision modelling approach for ranking applicant CVs consists of ***four phases*** of operation as shown in Fig. 2.

In **phase 1** of the proposed system, a selection panel of experts are chosen and each expert is asked to select the characteristics which they think should form the requirements criteria of the person specification for the given job role. From examining actual written person specifications for different job posts, we have found that the requirements criteria are usually split into the three

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categories of: '*Essential*', '*Preferred*' and '*Desired*'. Most employers would rank applicants on the basis that they initially satisfy the '*Essential*' characteristics for the job followed by the '*Preferred*' and finally the '*Desired*' characteristics. The '*Essential*' characteristics would therefore be given a higher significance and weighting than the '*Preferred*' characteristics which would also be given a higher significance and weighting than the '*Desired*' characteristics. Our system therefore uses this categorising scheme for asking the experts to select and categorise their characteristics for the person specification.

The experts are then asked to rate the importance of the characteristics they selected for each requirement category on a predefined scale. Experts would use an intuitive online web-based interface for completing the selection and rating of characteristics in phase 1.

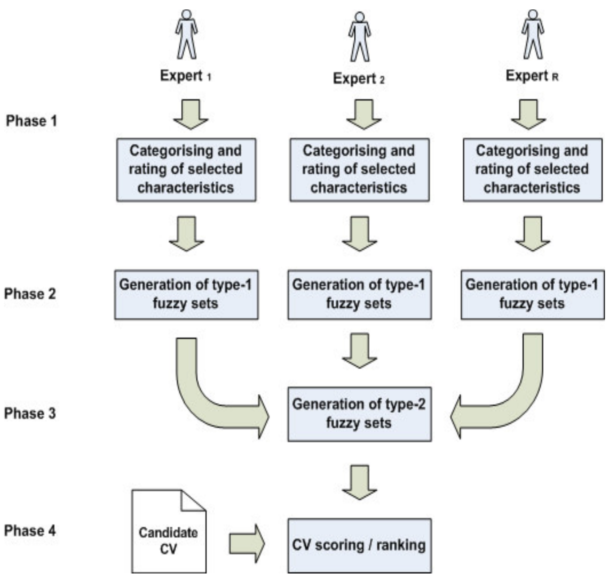


Fig. 2. A flow diagram showing the main phases of type-2 fuzzy CV ranking system.

In our system an applicant CV is ranked according to the three linguistic labels: '*Poor*', '*Moderate*' and '*Good*' that describe the degree to which skills in the CV match the characteristics defined in the person specification.

In **phase 2,** the categorised and rated characteristics defining each expert's person specification are used to generate type-1 fuzzy sets that describe the three linguistic labels for ranking the applicant CVs according to that expert's preferences. As each expert will have varying preferences, the shape and size of their generated type-1 fuzzy sets will also be different due to the uncertainties in the meaning of the linguistic labels between different experts [7].

In **phase 3,** interval type-2 fuzzy sets are generated for the linguistic labels by aggregating the type-1 fuzzy sets for each expert using a union operation leading to the FOU for each linguistic label [5]. The FOU of the type-2 sets model the uncertainties between the experts in the group and will be used to rank the scored applicant CVs.

In **phase 4,** the CVs are scored according to a scoring scheme based on the categorised and rated characteristics selected by each expert. The scores are aggregated and weighted using a weighting factor that is based on the significance placed on each of the three requirements categories for selecting applicants. The final score for each CV is then mapped to the type-2 fuzzy sets to get the linguistic ranking for the CV.

The following four subsections will discuss the various four phases involved in our system.

A. Phase 1: Categorising and Rating of Selected Characteristics

Phase 1 starts with a selection panel of *R* experts. We denote each expert as E_k where *k*=1 to *R*. *L* is the set of occupation specific characteristics which contains *N* characteristics c_i where *i*=1 to *N*. From the set *L* each expert E_k is asked to select her/his choices of the characteristics for the three requirement categories ('*Essential*', '*Preferred*' and '*Desired*') in our categorising scheme. We formally denote each category as C_j where *j*=1 to 3 is the index for the categories: '*Essential*', '*Preferred*' and '*Desired*' respectively. The expert selects Q_{jk} unique characteristics c_{mjk} (from the set *L*) for each category C_{jk} where $0 < Q_{jk} < N$ and *m*=1 to Q_{jk}. The expert numerically rates the importance of each selected characteristic c_{mjk} using a predefined rating scale. The importance rating for each characteristic c_{mjk} is denoted as r_{mjk}. Most job roles also have a '*Minimum*' or '***must have***' set of characteristics without which an applicant will not be considered for selection. This is fixed for the occupation domain and defined in advance. For example for a nursing job, the candidate should hold a nursing degree otherwise there is no need to look at the rest of her/his qualifications as she/he does not satisfy the minimum requirements for this job.

We denote this as a subset Minimum characteristics $L_{(\text{minimum})}$ of *L* comprising of *U* characteristics c_p where $1 < p < U$. The importance ratings for the characteristics in $L_{(\text{minimum})}$ can also be set by each expert where the importance rating of each '*Minimum'* required characteristic c_p is denoted as r_{pk}.

From the process described above each expert E_k produces a completed person specification that categories and rates the importance of their preferences on the '*Minimum*', '*Essential*', '*Preferred*' and '*Desired*' characteristics. Fig. 3 describes the process flow for phase 1.

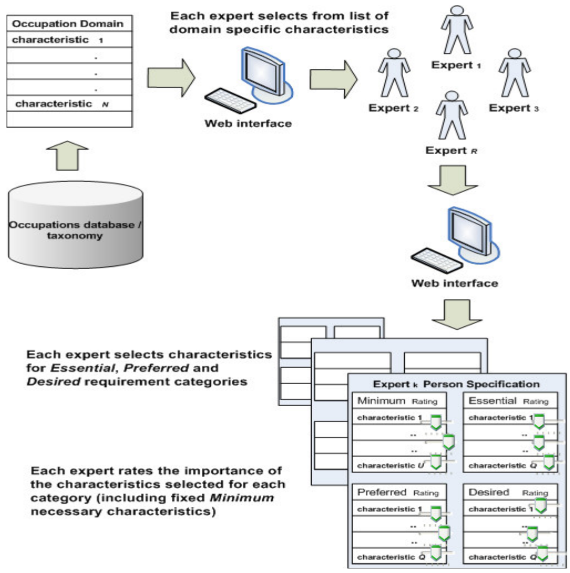


Fig. 3. Flow diagram showing the process for categorizing and rating an expert's selected characteristics.

B. Phase 2: Generation of Type-1 Fuzzy Sets

In phase 2 the categorised and rated characteristics for each expert E_k are used to generate the parameters for type-1 MFs that represent the fuzzy sets associated with the linguistic labels '*Poor*', '*Moderate*' and '*Good*' based on the expert's preferences. More formally A_s^k is a type-1 fuzzy set associated with a linguistic label *s* where *s*=1 to 3 is the index for the labels: '*Poor*', '*Moderate*' and '*Good*' respectively for each expert E_k. In our system the shapes of the type-1 membership functions for each type-1 fuzzy set are based on left shoulder (for '*Poor*' candidate), non-symmetric triangular (for '*Moderate*' candidate), and right shoulder (for '*Good*' candidates) MFs respectively as shown in Fig. 4 where *M* is the maximum range of the MFs. The parameters $[a_{MF}, b_{MF}]$ denote the left and right defining points of the support of a MF, as shown in Fig. 4. In the case of the non-symmetric triangular type-1 membership function (for *Moderate* candidate) the point for the MF equalling to 1 is denoted as e (see Fig. 4b). The parameters $[a^k_{MF_{(s)}}, b^k_{MF_{(s)}}]$ and $e^k_{(2)}$ for each type-1 MF are derived directly from the categorised and rated requirement characteristics supplied by each expert E_k and are calculated as follows:

For Left shoulder MF.

$$a^k_{MF_{(1)}} = \sum_{p=1}^{U} r_{pk} \tag{2}$$

$$b^k_{MF_{(1)}} = \sum_{m=1}^{Q_{1k}} r_{m1k} \tag{3}$$

For the Triangular MF:

$$a^k_{MF_{(2)}} = a^k_{MF_{(1)}} \tag{4}$$

$$b^k_{MF_{(2)}} = b^k_{MF_{(1)}} + \sum_{m=1}^{Q_{2k}} r_{m2k} \tag{5}$$

$$e^k_{(2)} = b^k_{MF_{(1)}} \tag{6}$$

For the Right shoulder MF:

$$a^k_{MF_{(3)}} = b^k_{MF_{(1)}} \tag{7}$$

$$b^k_{MF_{(3)}} = b^k_{MF_{(2)}} \tag{8}$$

Based on Equations (2), (3), (4) (5), (6), (7) and (8) the generated type-1 fuzzy sets for an expert E_k will conform with the required guidelines in HR systems where an applicant CV will receive a maximum membership in the type-1 fuzzy set for '***Moderate***' if it contains all the '*Essential*' rated characteristics and will only receive a maximum membership in the type-1 fuzzy set for '***Good***' if it contains the combination of all the '*Essential*' and '*Preferred*' plus some "*Desired*" characteristics. It should be noted that having the combination of all the '*Essential*' characteristics and some of the '*Preferred*' characteristics will lead to being on the boundary between the '***Moderate***' and '***Good***' sets.

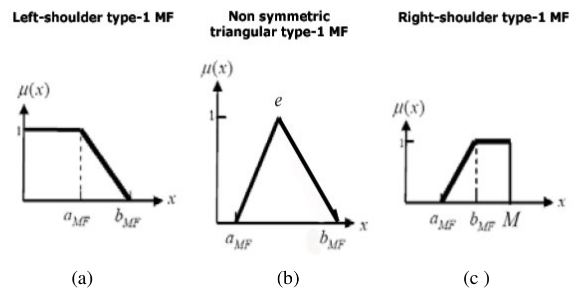


Fig. 4. (a) Type-1 left-shoulder MF. (b) Non symmetric triangular type-1 MF. (c) Right-shoulder type-1 MF [5].

C. Phase 3: Generation of Type-2 Fuzzy Sets

The type-1 fuzzy sets that are generated for each expert E_k in phase 2 are aggregated to create the FOU's for Interval type-2 fuzzy sets. Using the Representation Theorem [8], each Interval type-2 Fuzzy set $\tilde{A}_s$ is computed as:

$$\tilde{A}_s = \bigcup_{k=1}^{R} A_s^k \tag{9}$$

Where A_s^k is referred to as the k^{th} embedded type-1 fuzzy set and $\bigcup$ is the union operation [5]. The process of generating $\tilde{A}_s$ is based on approximating the upper MF ($\bar{\mu}_{\tilde{A}_s}(x)$) and the lower MF ($\underline{\mu}_{\tilde{A}_s}(x)$) of $\tilde{A}_s$. This will depend on shape of the embedded type-1 fuzzy sets and the

FOU model which is to be generated for $\tilde{A}_s$. In our system we use interior FOU models (shown in Fig. 5a) for approximating the upper and lower MF parameters from all the embedded non-symmetric triangular type-1 MFs (thus representing the '***Moderate***' category). The resulting interior interval type-2 fuzzy set is described by parameters: $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$, $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters: $\overline{a}_{MF}$, $\underline{b}_{MF}$ for a non-symmetric triangular lower MF, with an intersection point (d, μ_d) [5], as shown in Fig. 5a. Shoulder FOU models are used for approximating all the left and right shoulder embedded type-1 MFs. The resulting left and right shoulder interval type-2 fuzzy sets are described by the parameters: $\underline{a}_{MF}$, $\underline{b}_{MF}$, $\overline{a}_{MF}$ and $\overline{b}_{MF}$ to represent the upper and lower shoulder MFs [5], as shown in Fig. 5b and 5c respectively. The procedures for calculating these parameters are now described as follows:

1) FOU models for interior FOUs: Given the parameters for the symmetric triangular type-1 MFs generated for each of the k experts $[a^k_{MF_{(2)}}, b^k_{MF_{(2)}}]$ and $e^k_{(2)}$, the procedure for approximating the FOU model for interior FOUs is as follows [5]:

For the upper MF $\overline{\mu}_{\tilde{A}_{(2)}}(x)$ we need to follow the following steps:

(1) For $\mu(x) = 0$, find $\underline{a}_{MF}$ to be equal to the minimum $a^{\min}_{MF_{(2)}}$ of all left-end points $a^k_{MF_{(2)}}$ and $\overline{b}_{MF}$ to be equal to the maximum $b^{\max}_{MF_{(2)}}$ of all right-end points $b^k_{MF_{(2)}}$ [5]. (2) For $\mu(x) = 0$, find $\underline{c}_{MF}$ to be equal to the minimum $e^{\min}_{(2)}$ of the centres $e^k_{(2)}$ and $\overline{c}_{MF}$ to be equal to , maximum $e^{\max}_{(2)}$ of the centres $e^k_{(2)}$ (3). Approximate the upper MF $\overline{\mu}_{\tilde{A}_{(2)}}(x)$ by connecting the following points with straight lines: $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$, and $\overline{b}_{MF}$. The result is a trapezoidal upper MF as depicted in Fig. 5a.

The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}_{(2)}}(x)$ are as follows:

(1) For $\mu(x) = 0$, find $\underline{a}_{MF}$ to be equal to the maximum $a^{\max}_{MF_{(2)}}$ of all left-end points $a^k_{MF_{(2)}}$ and $\overline{b}_{MF}$ to be equal to the minimum $b^{\min}_{MF_{(2)}}$ of all right-end points $b^k_{MF_{(2)}}$ [5]. (2) Compute the intersection point (d, μ_d) by the following equations [5]:

$$d = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})} \quad (10)$$

$$\mu_d = (\underline{b}_{MF} - d) / \underline{b}_{MF} - \underline{c}_{MF}) \quad (11)$$

(3) Approximate the lower MF $\underline{\mu}_{\tilde{A}_{(2)}}(x)$ by connecting the following points with straight lines: $\overline{a}_{MF}$, d , and $\underline{b}_{MF}$. The result is a triangle lower MF as shown in Fig. 5a.

2) *FOU models for shoulder FOUs:* Given the parameters $[a^k_{MF_{(1)}}, b^k_{MF_{(1)}}]$ and $[a^k_{MF_{(3)}}, b^k_{MF_{(3)}}]$ for the respective left and right shoulder type-1 MFs generated for each of the k experts, the following is the procedure to approximate the FOU model for left-shoulder FOUs [5].

(1) For $\mu(x) = 0$, find $\overline{b}_{MF}$ to be equal to the maximum $b^{\max}_{MF_{(1)}}$ of all end points $b^k_{MF_{(1)}}$ [5]. (2) For $\mu(x) = 1$, find $\overline{a}_{MF}$ to be equal to the maximum $a^{\max}_{MF_{(1)}}$ of all end points $a^k_{MF_{(1)}}$ [5]. (3) Approximate the upper MF $\overline{\mu}_{\tilde{A}_{(1)}}(x)$ by connecting the following points with straight lines: (0:1), $(\overline{a}_{MF}, 1)$ and $(\overline{b}_{MF}, 0)$. The result is a left shoulder upper MF as depicted in Fig. 4b

The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}_{(1)}}(x)$ are as follows: (1) For $\mu(x) = 0$, find $\underline{b}_{MF}$ to be equal to the minimum $b^{\min}_{MF_{(1)}}$ of all end points $b^k_{MF_{(1)}}$ [5]. (2) For $\mu(x) = 1$, find $\underline{a}_{MF}$ to be equal to the minimum $a^{\min}_{MF_{(1)}}$ of all end points $a^k_{MF_{(1)}}$ [5]. (3) Approximate the lower $\underline{\mu}_{\tilde{A}_{(1)}}(x)$ by connecting the following points with straight lines: (0:1), $(\underline{a}_{MF}, 1)$ and $(\underline{b}_{MF}, 0)$. The result is a left shoulder lower MF as shown in Fig. 5b.

The procedure for approximating a FOU model for right-shoulder FOUs is similar to the one for left-shoulder FOUs. The upper MF $\overline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated as follows: For $\mu(x) = 0$, $\underline{a}_{MF}$ = $a^{\min}_{MF_{(3)}}$ and for $\mu(x) = 1$, $\underline{b}_{MF}$ = $b^{\min}_{MF_{(3)}}$. Therefore the resulting right shoulder upper MF $\overline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated by connecting the following points with straight lines: $(\overline{a}_{MF}, 0)$ $(\overline{b}_{MF}, 1)$ and $(M, 1)$, depicted in Fig. 5c. The lower MF $\underline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated as follows: For $\mu(x) = 0$, $\overline{a}_{MF} = a^{\max}_{MF_{(3)}}$ and for $\mu(x) = 1$, $\overline{b}_{MF}$ = $b^{\max}_{MF_{(3)}}$. Therefore the resulting right shoulder lower MF $\underline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated by connecting the following points with straight lines: $(\overline{a}_{MF}, 0)$, $(\overline{b}_{MF}, 1)$ and $(M, 1)$ as shown in Fig. 5c.

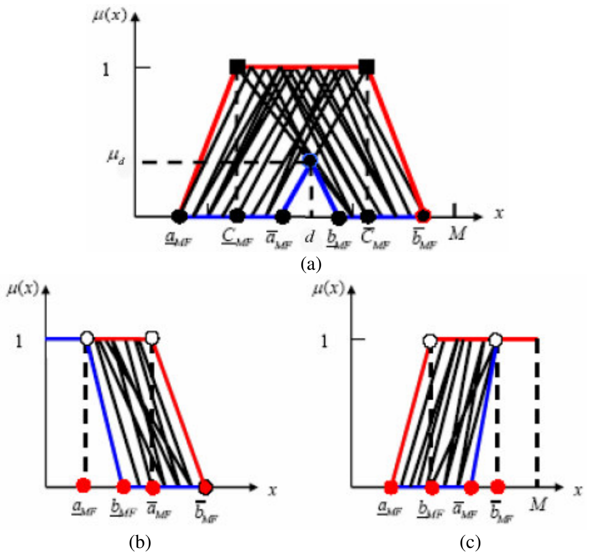


Fig. 5. a) An interior type-2 MF embedding the different type-1 triangle MFs. b) A left shoulder type-2 MF embedding different left shoulder type-1 MFs. c) A right shoulder type-2 MF embedding different right shoulder type-1 MFs.

D. Phase 4: CV Scoring and Ranking

The process of ranking an applicant CV is based on comparing the skill characteristics extracted from the CV with the rated and categorised characteristics defined by each expert. Skill characteristics can be extracted from an electronically formatted CV using language processing and information extraction techniques. The extracted skill characteristics are then scored using a scoring method (depicted in Fig. 6) which we will describe in the following paragraphs.

A CV can be formally defined as a set of W skills characteristics c_h where h=1 to W. Each skill characteristic c_h is compared to the characteristics c_{mjk} which have been selected by each expert E_k to see if there is a match ($c_h == c_{mjk}$). Each matching skill characteristic is denoted as c_x where $c_x = c_h = c_{mjk}$ and x=1 to W_x where W_x is the number of matching characteristics. For each matching skill characteristic c_x (belonging originally to characteristic m in category j), the average rating score among all the experts who selected it, is calculated as follows:

$$AVr_x = \frac{\sum_{k=1}^{V} r_{mjk}}{V} \tag{12}$$

where V is the number of experts that selected and rated c_x. Not all the experts may categorise c_x with the same requirements category. The requirement category that AVr_x will be assigned to is therefore chosen as the most frequently occurring category C_j which the V experts had selected for categorising c_x. For each requirements category C_j, the assigned average rating scores AVr_{xj} are aggregated to produce a total category score Cs_j which is weighted using a predefined weighting factor w_j based on the significance that is given to the C_j category in the selection process. The final score for a CV is then calculated as follows:

$$FRs = \sum_{j=1}^{3} (Cs_j w_j) \tag{13}$$

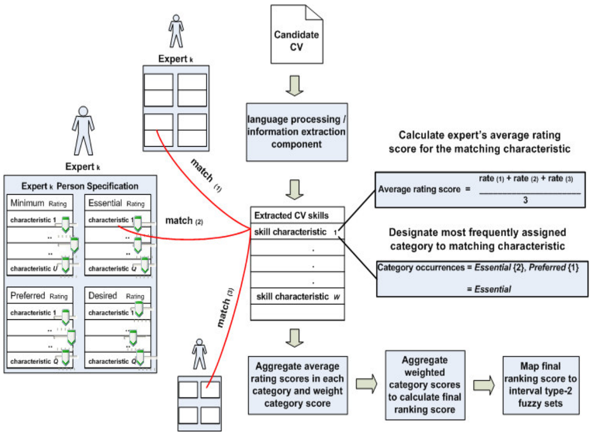


Fig. 6. Flow diagram showing the process for scoring and ranking CVs.

The final ranking score *FRs* will be mapped to each type-2 fuzzy set $\tilde{A}_s$ to determine the membership degree of the CV to each type-2 fuzzy set. The membership degree is calculated as the centre of gravity of the interval membership of $\tilde{A}_s$ at x as follows [7]:

$$\mu_{\tilde{A}_s}^{cg}(x) = f_x^{cg}(\tilde{A}_s) = \frac{1}{2}\left[\bar{\mu}_{\tilde{A}_s}(x) + \underline{\mu}_{\tilde{A}_s}(x)\right] \tag{14}$$

where $x = FRs$.

The type-2 fuzzy set with the highest interval membership is selected for ranking the CV as follows:

$$\mu_{\tilde{A}_s^{q*}}^{cg}(x) \geq \mu_{\tilde{A}_s^{q}}^{cg}(x) \tag{15}$$

where $q^* \in \{1,\ldots 3\}$.

The type-2 fuzzy sets provide a methodology for representing the ranking decisions for the CV in terms of linguistic labels which are easily understandable by the human user. The scoring scheme provides a transparent break down of how each skill characteristic in the CV is categorised and rated by the selection panel of experts. This can be used to provide justification for the systems selection and ranking decisions.

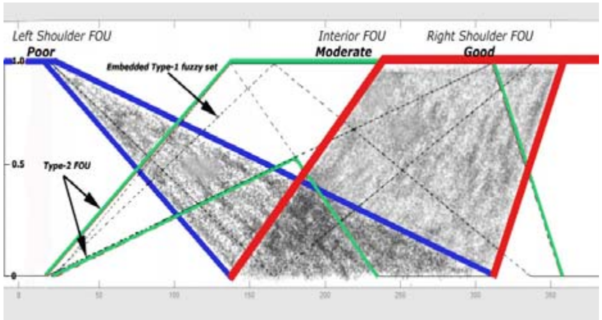
IV. Experiments and Results

We have performed unique experiments in which our type-2 fuzzy approach for modelling group decisions has been used to capture the job role requirements preferences from a selection panel of three experts within the health and social care occupation domain. The system modelled the uncertainties within the experts panel using interval type-2 fuzzy sets. Our system was evaluated based on the ranking decisions it produced for four applicants CVs when compared with those of the human experts.

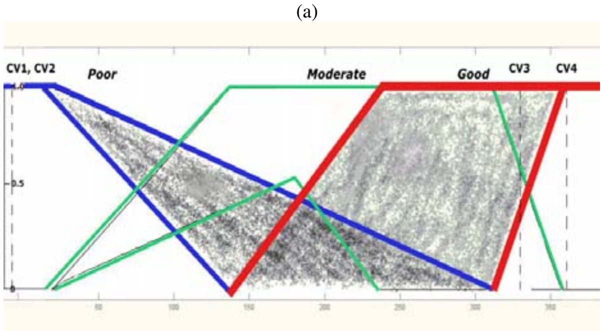
The job role for which the person specification had to be created was for a Registered General Nurse (RGN) Care Home Manager for a 90 bed care home with 80 Dementia and 10 mental health patients. The three domain experts in the selection panel comprised of an HR Manager, Operations Manager and a Managing Director of a care agency. The three experts were each asked to select from a list of 87 occupation specific requirement, characteristics pertaining to a RGN Care Manager. The characteristics were grouped into general and specific experiences, soft & basic skills, licenses, registration & checks, working knowledge, qualifications, training and years of management experience.

Each expert in the selection panel was asked to select characteristics for the three requirements categories: '*Essential*', '*Preferred*' and '*Desired*'; then rate the importance of their selected characteristics for each category on a scale from 1 to 10, as described in phase 1. The '*Minimum*' required characteristics for the job role were predefined as a Nursing Qualification pertaining to either a RGN or Registered Mental Nurse (RMN). A person specification for the job role was therefore produced by each expert that comprised of their preferences for the requirement characteristics an applicant should possess. The categorised and rated characteristics selected by each expert were used to generate the parameters for the left shoulder, non-symmetric triangular and right shoulder type-1 fuzzy sets associated with the linguistic labels for '*Poor*', '*Moderate*' and '*Good*' as explained in phase 2. The embedded type-1 fuzzy sets for each user were aggregated to generate shoulder and interior FOU models for the interval type-2 fuzzy sets used by our system to rank the applicant CVs as described in phase 3. Fig. 7a shows the interval type-2 FOUs (with the embedded type-1 fuzzy sets drawn as thin dashed lines) generated from each expert's requirements preferences.

Four applicant CVs were used to evaluate the performance of the system. The skills characteristics described in each CV were extracted and scored using the scoring scheme described in phase 4. The scores for each CV were mapped to the interval type-2 fuzzy sets to determine the ranking for each CV based on calculating their memberships to the type-2 fuzzy sets, as is shown in Fig. 7b. Each of the three experts in the selection panel was separately asked to manually rank the CVs according to the same linguistic labels: *Poor*, *Moderate* and *Good* associated with the type-2 fuzzy sets generated by the system.



(a)



(b)

Fig. 7. a) The generated interval type-2 FOUs. b) CVs ranked against generated type-2 fuzzy sets.

Table I shows the final scores and ranking decisions of each CV by our system compared with the ranking decisions of the three human experts. Both CV1 and CV2 were ranked by the system as '*Poor*', receiving a default score of 0 as neither CV satisfied all the '*Minimum*' requirement characteristics. CV3 and CV4 were both ranked as '*Good*', where CV4 was scored higher than CV3. The results show that the ranking decisions of the system are consistent with those of the human experts. For CV1 and CV2, the majority of two out of the three experts ranked them as '*Poor*' with the remaining expert ranking both the CVs as '*Moderate*'. This decision is however overridden by the fact that both CVs did not satisfy the '*Minimum*' required characteristics. CV3 was ranked as '*Good*; by two of the experts with a single expert ranking it as '*Moderate*'. The systems score for CV3 accounts for this difference of opinion between the experts when mapped to the type-2 fuzzy sets. As can be seen from Fig. 7b the score for CV3 has the highest membership in the type-2 set for *Good* but also has a low membership in the '*Moderate*' set, which models the panels ranking decisions. CV4 is ranked as '*Good*' by all three of the experts which match the systems decision as shown in Fig. 7b. Although the final scores for CV1 and CV2 were defaulted to 0, the system could provide users with scores for these CVs to identify and rank potential candidates who may be able to fulfil the '*Minimum*' requirements through additional training in the future.

TABLE I
SCORING AND RANKING DECISIONS OF SYSTEM AND HUMAN EXPERTS

	System scoring and ranking decisions		Human expert ranking decisions		
CV	**Score**	**Rank**	**Expert1 Rank**	**Expert2 Rank**	**Expert3 Rank**
CV1	0	*Poor*	*Poor*	*Poor*	*Moderate*
CV2	0	*Poor*	*Poor*	*Poor*	*Moderate*
CV3	332.22	*Good*	*Moderate*	*Good*	*Good*
CV4	359.83	*Good*	*Good*	*Good*	*Good*

V. CONCLUSIONS

In this paper, we presented a type-2 fuzzy based system that enabled automating the processes of requirements specification and applicant matching/ranking in HR systems. To the author's knowledge, the developed system can be regarded as the first type-2 based commercial software product.

The system can capture the job requirements preferences from the panel of experts to generate a person specification that reflects the collective opinion of the experts in a consistent and objective way. Type-2 fuzzy sets were used to model the uncertainties arising due to the varying preferences of each expert in a selection panel. A scoring method was used to score the applicant CVs based on how closely they match the requirements preferences. The scores are matched to the type-2 fuzzy sets to determine a linguistic ranking for the CVs.

The paper has presented experiments for an RGN Care Home Manager job in which the system has elicited requirement preferences from a selection panel of three domain experts. Type-2 fuzzy sets were generated to model uncertainties within the collective preferences of the panel. The system was evaluated by scoring and ranking four real applicant CVs and comparing its ranking decisions with those of the human experts. The results showed that our approach was able to accurately model the group's ranking decisions for each applicant CV. The system produces linguistic ranking decisions which are easy for a human end user to understand and the scoring method can be used to produce any legally required justification for all ranking decisions.

For our current and future work, we are working on integrating the developed system with text parsing systems to facilitate the capture of the applicants' skills from even unstructured CVs. We are also working with integrating the presented system with different consensus modelling systems.

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