A Neuro-Fuzzy Based Agent for Group Decision Support in Applicant Ranking within Human Resources Systems

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A Neuro-Fuzzy Based Agent for Group Decision Support in Applicant Ranking within Human Resources Systems

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***Abstract*—Applicant selection and ranking methods for job roles within Human Resources (HR) systems involve high levels of uncertainty. This is due to the requirement to allow for the varying opinions and preferences of the different occupation domain experts in the decision making process. Hence, there is a need to develop novel systems that will enable HR departments to determine the most important requirements criteria (experience, skills etc) for a given job, based on the preferences of different domain experts, while ensuring that the experts decisions are unbiased and correctly weighted according to their knowledge and experience. This will enable a more effective way to short list submitted candidate CVs from a large number of applicants providing a consistent and fair CV ranking policy, which can be legally justified. This paper presents a novel system using a neuro-fuzzy based agent approach for automatically determining the key skill characteristics defining each expert's preferences and ranking decisions, while handling the uncertainties and inconsistencies in group decisions of a panel of experts. The presented system automates the processes of requirements specification and applicant's ranking. Experiments have been performed within the residential care sector where the proposed system has been shown to produce ranking decisions that were relatively highly consistent with those of the human experts.**

I. Introduction

The current global economic crisis means that companies today are faced with the dilemma of having far less capital to invest within their HR divisions, while equally needing to ensure they are selecting the most competent and qualified applicants suited for job vacancies. This might result in companies being forced to employ a reduced, more agile, productive and cost effective workforce.

Due to the shrinking job market and higher volume of job seekers, it is necessary to effectively short-list and rank candidates for the particular job role. This is based on matching the applicant's profile and Curriculum Vitae (CV) against the requirements criteria (experience, skills, knowledge, qualifications, etc) which the post holder needs in order to perform the duties of the job [15]. This process is usually conducted by recruitment personal and also involves experts from within the job area.

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One of the problems within many corporations is that there is no systematic and consistent process for specifying the jobs requirements criteria and the ranking policy. There are now financial and legal considerations involved in the selection of new employees. The expense of recruiting the wrong candidate has made many companies become far more concerned about conducting their candidate selection process in a more cost effective way. In recent years within the UK, USA and the European Union, there has been new legislations requiring employers to provide clear reasons for short-listing or rejecting job applicants based on assessing how much of the job requirements criteria the applicants satisfy [6]. Hence, accurately identifying the key 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 can be used to provide a justification for the selection decisions [6].

The organisation's Human Resources (HR) manager has the task of formulating a person specification (job requirement) for a given job role. 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 and it is not always clear without observing the expert's decision making behaviour which characteristics most influence a ranking decision.

Due to the varying knowledge and experiences of different experts, not all experts will be consistent in their opinions and in applying their preferences for consistently ranking different applicants with similar abilities in the same way. It is therefore important to identify and weigh higher the opinions of more reliable and experienced experts over those who are less consistent in their decision making behaviour.

The variations in the opinions and consistencies of different experts cause high degrees 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 the experts 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 an objective way. The difficulty increases for big multinational organisations where distributed experts need to collaborate to develop an international advert for a given job role.

Fuzzy systems offer a methodology for consensus modelling and aggregating the preferences of different experts as described in [3], [5], [8], [9], [10], [12]. These approaches however do not aim to model and handle the inconsistencies and uncertainties between the opinions and preferences of different experts involved within the group decision and consensus modelling process. There are several systems in the literature that use fuzzy decision making for human resources and personal selection [14], [17], [21]. These systems however do not model the group decision making processes of different experts involved within the requirements specification and ranking processes.

To provide an effective ranking policy for applicant CVs it is important to determine which key skill characteristics best characterise each experts ranking decisions. This can be defined as a process, which needs to identify the most important skills for classifying these ranking decisions, and this can have a significant impact on the classification of the ranking decisions to provide correct ranking of applicant CVs. The performance of the ranking classification can be degraded if irrelevant or redundant features are selected. The previous approaches that have been outlined above do not identify the most important skill characteristics influencing a given experts' decisions.

Various feature selection methods have been proposed to address the selection of the most relevant features for a classification task. In [4] [13] decision trees are applied to find relevant features by keeping only those that appear in the decision tree. Principle Component Analysis [20] is used to reduce complex data with a large number of attributes into lower dimensions to determine subtle features within the data. These approaches however do not provide a means showing the degree of influence and affect each input skill has on the ranking decisions.

Feature weighting is an approach that seeks to estimate the relative importance of each feature (with respect to the classification task), and assign it a corresponding weight [23]. It is suitable for tasks in which the relevance of the attributes needs to be determined [23]. Several examples of feature weighting approaches can be found in [1] [19] [22].

Neural Networks can be used as a method for feature weighting where by the importance of a feature is extracted based on the strengths (weights) of related links in a trained neural network. A major advantage of using neural networks is due to their capacity to act as universal appoximators [11]. Neural networks therefore have the potential to better capture the most relevant features related to a classification task [23].

In this paper, we present a novel technique for automating the process of ranking applicants' CVs by employing a neuro-fuzzy based agent approach. The system creates a person specification using neural networks to automatically identify the most important job role requirement characteristics based on the preferences and ranking decisions from the group of experts. Fuzzy sets are used for modelling the uncertainties and varying consistencies between the experts' preferences.

A scoring method is proposed that scores applicant's CVs based on how well they match the key requirements preferences of each expert. The scores are mapped to the fuzzy sets to determine the ranking of the different CVs. We will present real world experiments in the care domain where our system handled the uncertainties and produced ranking decisions that are relatively highly 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 fuzzy sets. Section III gives an introduction to neural networks. Section IV will describe our neuro-fuzzy group decision modelling and CV ranking technique. In Section V, we will present the experiments and results. Finally conclusions are presented in Section VI.

II. Fuzzy Sets

The process of human decision making is naturally uncertain due to the inherent subjectivity and vagueness in the articulation and aggregation of human opinions and preferences. Fuzzy sets provide a methodology for computing with words by handling these uncertainties using linguistic quantifiers such as "*High*" or "*A lot*" [16]. Fuzzy sets therefore provide a tolerance for imprecision which can be exploited to achieve tractable, robust and low cost systems. Formally a fuzzy set is defined as follows:

Given a domain of discourse *X*, a fuzzy set *A* on *X* is a set expressed by a characteristic function ${}_A(x) : X \rightarrow [0,1]$ that measures the membership grade of the elements in X belonging to the set *A*.

$$A = \{(x, \ {}_A(x)) \mid \forall x \in X, \ {}_A(x) \in [0,1]\} \qquad (1)$$

where ${}_A(x)$ is called the Membership Function (MF) of the fuzzy set *A*.

III. Neural Networks

Artificial Neural Networks (ANNs) are an information processing paradigm that is inspired by the way in which biological nervous systems such as the brain process information. The key element of this paradigm is the novel structure of the information processing system. This system is composed of large number of highly interconnected processing elements called neurons, which work in unison to solve specific problems [2].

In a similar way to people ANN's can also learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Using a supervised training algorithm such as backpropagation [18] the network can automatically learn the structure or classification of the data. This learning process adjusts to the synaptic connections or weights that exist between the neurons. Given a set of training data (input and output pairs) (x, y), where $x \in X$, and $y \in Y$; the aim is to find a function $f : X \rightarrow Y$ in the allowed class of functions that approximates the mapping between the inputs and outputs implied by the data. It has been shown that ANN's are universal approximators [11]. The topology of the multilayer feed forward ANN that is employed in this paper has an input layer, single hidden layer and an output layer with a single output.

IV. The Neuro-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 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 neuro-fuzzy group decision modelling and ranking approach consists of ***five phases*** of operation as shown in Fig. 1a.

In **phase 1** each expert initially selects a subset of occupation characteristics which they think should form the requirements criteria of the person specification for the given job role. Experts use an intuitive online web-based interface for completing the selection of their person specification characteristics.

In **phase 2** training data is collected from each recruitment expert on their ranking decisions for a sample set of candidate CVs. Each expert assesses and ranks the CVs based on the subjective person specification characteristics they have specified in phase 1. In our system an applicant CV is ranked according to the three linguistic labels: '*Poor*', '*Moderate*' and '*Good*' that indicate the degree to which the skills possessed by the candidate, meet the requirements defined in the person specification. A web-based interface is used to allow experts to review each CV and record their ranking decisions, which can be unobtrusively incorporated into their regular CV review and assessment decision making process.

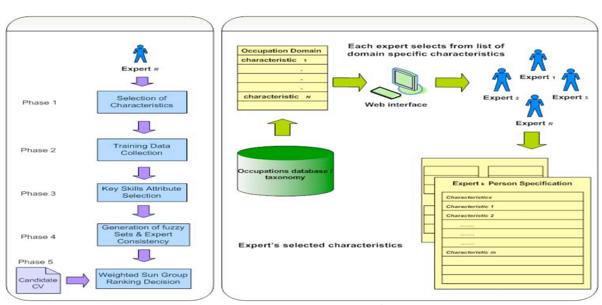

Fig. 1. a) A flow diagram showing the main phases of the neuro-fuzzy group decision modelling and CV ranking system. b) Flow diagram showing the process for selecting and rating an expert's characteristics.

In **phase 3** a neural network feature weighting method [23] is used to analyse the training data collected from each expert. The skills present in the sample CVs that match the expert's requirements criteria are weighted using the neural network training algorithm to determine the key skill attributes that classify the three ranking decisions.

In **phase 4,** the selected skill attributes characterising each expert's ranking decisions are used to generate fuzzy sets that describe the three linguistic labels for ranking the applicant CVs. As each expert will have varying preferences, the shape and size of their generated fuzzy sets will also be different due to the uncertainties in the meaning of the linguistic labels between different experts [16].

The consistency of each expert's ranking behaviour is validated over the sample set of CVs. The generated fuzzy sets for the three linguistic labels are used to rank the sample CVs. The fuzzy ranking decisions generated by the system are then compared with the expert's own ranking of the CVs. This determines a numerical coefficient of how consistent the expert is in ranking the CVs according to the skill preferences they are using to characterise their ranking decisions.

In **phase 5,** new CVs are scored based on comparing their extracted skills with the rated skill attributes characterising each expert's ranking decisions. The final score for each CV is then mapped to the fuzzy sets modelling each expert's linguistic ranking decisions, which are also weighted by the expert's consistency coefficient. The system then aggregates the weighted fuzzy mappings together for each expert to derive an overall ranking for the CV based on the group decision. The system can be adaptive to the different job roles or the changing opinions and preferences of the experts. Phases 1 to 4 can be periodically repeated or run in parallel based on evaluating and feeding back the system's ranking decisions to improve its accuracy.

The following five subsections will discuss these five different phases involved in our system.

A. Phase 1: Selection and Rating of Characteristics

Phase 1 will start with a selection panel of R experts. We denote each expert as E_k where k=1 to R. N is the set of occupation specific characteristics c_a where a=1 to N. From the set N each expert E_k is asked to select her/his choices of the characteristics. The expert selects Q_k unique characteristics c_{mk} (from the set N) where $0 < Q_k < N$ and m=1 to Q_k. 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.

From the process described above each expert E_k produces a completed person specification that rates the importance of their preferences on the job role characteristics. Fig. 1b describes phase 1's process flow.

B. Phase 2: Training Data Collection

In phase 2 training data is collected from each recruitment expert on their ranking decisions for a sample set of T

candidate CVs where j=1 to T. The process of ranking an applicant CV is based on comparing the skill characteristics extracted from the CV with the characteristics defined by each expert. Skill characteristics can be extracted from an electronically formatted CV using language processing and information extraction techniques. Any CV that does not satisfy the minimum requirements is automatically excluded from the process at this stage.

A CV j can be formally defined as a set of extracted skills characteristics c_{hj} where h=1 to W_j. Each skill characteristic c_{hj} is compared to the characteristics c_{mk}, which have been selected by each expert E_k to see if there is a match ($c_{hj} == c_{mk}$). Each matching skill characteristic is denoted as c_{xjk} where $c_{xjk} = c_{hj} = c_{mk}$ and x=1 to C_{jk} where C_{jk} is the number of matching characteristics for the jth training CV.

The Expert is then presented with the extracted skills from the candidate CV where she/he can review and electronically rank the CV according to the three linguistic labels: '*Poor*', '*Moderate*' and '*Good*' that describe the ranking decisions.

C. Phase 3: Key Skills Attributes Selection

Most employers rank applicants based on the characteristics of the predefined categories of: '*Essential*' '*Preferred*' and '*Desired*'. 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. However we have observed that experts will rank candidates based on implicitly selecting and grouping skills together that best influence each of their ranking decisions. These skill groupings cannot be predefined by the expert and can only be discovered from observing the experts decision making behaviour across a sample group of CVs.

In phase 3, a neural network based feature weighting method [23] is used to analyse the training data collected from each expert in phase 2, to determine the skill attributes that best characterise their ranking decisions.

For each expert E_k the T CVs are classified according to the linguistic ranking decisions s where s = 1 to 3, corresponding to the index of the three ranking decisions: '*Poor*', '*Moderate*' and '*Good*'. A dataset d_s is produced for each ranking decision where the inputs m correspond to the Q_k skills characteristics selected by the expert and have the value $\in$ {0,1} denoting the presence or absence of the characteristic in the jth CV. There is a single output z_s, which has a value $\in$ {0,1} corresponding to the wither or not the jth CV is classified by the linguistic ranking decision s.

A multilayer backpropagation neural network net_s is created for each linguistic label s. The dataset d_s is divided into two subsets: a training set d_{s_1} (2/3 of d_s) and a testing set d_{s_2} (1/3 of d_s). The network is trained on d_{s_1} and its accuracy is estimated on d_{s_2}. The purpose of the testing set is to estimate the accuracy on an independent dataset (instead of the training set itself) in order to avoid over fitting the training data [23].

The network topology comprises of an input and output layer with single hidden layer as shown in Fig 1. The number of hidden nodes H is automatically determined by determining its accuracy on d_{s_2}. H is initially set to 1. After training for a fixed H, the network accuracy on the testing set d_{s_2} is recorded and H is incremented by 1. This continues until finding the best H by the following criterion: if H gives a best result while H +1 and H +2 do not yield a better result, then H is considered to be the best number of hidden nodes [23]. After determining the best H the whole training set d_s (to better utilize available training data) is applied to train a network with a fixed H (starting from the saved trained weight settings of the best H) [23].

After the training, the feature weighting is extracted from the trained network as follows: For an input node m its feature weight is given by [23]:

$$r_{mks} = \sum_{b=1}^{H} | V_{ib} \times V_{bz_s} | \tag{2}$$

In the above equation, r_{mks} is the feature weight for input node m; V_{ib} is the network weight (link strength) from input node m to the hidden node b, and V_{bz_s} is the weight from the hidden node b to the output node z_s; H is the number of hidden nodes. Each term in Equation (2) represents one path from an input node m to the output node z_s, through a hidden node b. The summation covers all possible forward paths from input node m to the output node. The rational for Equation (2) is that if a feature is important, it will have more influence on the output node by propagating forward through the hidden nodes. Such influence is reflected in the strengths of links along all the related paths. Equation (2) gives a quantified overall measure on the influence of each input attribute on the output ranking decision [23].

The trained neural network estimates the relative importance or weight r_{mks} of each skill characteristic c_{mk} based on strengths (weights) of related links in the network, in which an important skill is typically connected to strong links and has more impact on the output ranking decision s. A more important characteristic would therefore receive a larger weight than less important or irrelevant characteristic.

The derived weights r_{mks} for the skill attributes Q_k are ordered and normalized. A predefined threshold value is used to eliminate irrelevant attributes to determine the three subsets Q_{ks} of skill characteristics c_{eks} and their corresponding weight values r_{eks} where e=1 to Q_{ks}. The attributes Q_{ks} best characterise the linguistic ranking decision *s*. Unlike other feature selection and dimensionality reduction methods this approach provides feature extraction with weights showing the degree of influence and affect each input attribute has on the output decision; providing justification for the systems ranking decisions.

D. Phase 4: Generation of Fuzzy Sets & Expert Consistency

In phase 4 for each expert E_k the weighted characteristics Q_{ks} selected for the three ranking decisions are used to generate the parameters for MFs representing the fuzzy sets associated with the linguistic labels '*Poor*', '*Moderate*' and '*Good*'. More formally A_s^k is a fuzzy set associated with the linguistic label *s* for each expert E_k. In our system the shapes of the membership functions for each fuzzy set are based on right shoulder MFs. The parameters $[a_{MF}, b_{MF}]$ denote the left and right defining points of the support of a MF. The parameters $[a^k_{MF_{(s)}}, b^k_{MF_{(s)}}]$ for each MF are derived directly from the weight values of the selected requirement characteristics Q_{ks} for expert E_k and are calculated as follows:

Right shoulder MF parameters:

$$a^k_{MF_{(s)}} = \min(r_{eks}) \tag{3}$$

$$b^k_{MF_{(s)}} = \sum_{e=1}^{Q_{ks}} r_{eks} \tag{4}$$

The generated fuzzy sets can model the selected skill attributes from the expert's preferences that best characterise their ranking decisions and are used to rank candidates for the job role. A weighted consistency coefficient of each expert's ranking behaviour is determined from mapping the sample set of T CVs onto the fuzzy sets modelling the expert's ranking decisions. The ranking decisions determined from the fuzzy sets are compared with the expert's own ranking decisions from the training CVs recorded in phase 2. From this a weighted consistency coefficient $WCon_k$ is calculated using the approach described in [7].

E. Phase 5: Weighted Sum Group Ranking Decision

The system can now rank new candidate CVs based on a fuzzy group decision model derived from the experts. Skills are first extracted from the candidate's CV and compared against the weighted skill attributes characterising each expert's ranking decisions. Hence, the CVs are scored to derive aggregated ranking scores Agr_{ks} pertaining to each of the three ranking decisions *s* using a scoring scheme as described in [7].

The membership functions of the fuzzy sets A_s^k pertaining to each expert are weighted according to the expert's consistency coefficient as we have described in [7]. This influences the impact the expert's judgment will have in the final group decision. The most consistent experts will be given a higher weighting in ranking the candidate CVs than those who's ranking behaviour was least consistent.

The final group ranking decision for the CV is derived as follows: The fuzzy membership values from mapping the aggregated ranking scores Agr_{ks} to their corresponding fuzzy set A_s^k are calculated for each expert. A weighted sum of the fuzzy memberships to A_s^k for all the experts is then calculated as we have explained in [7]. The fuzzy set with the highest weighted sum membership is selected for ranking the CV.

The fuzzy sets provide a methodology for representing the ranking decisions for the CV in terms of linguistic labels that are easily understandable by the human user. The scoring scheme provides a transparent break down of how the importance of each skill characteristic in the CV is weighted by the group of domain experts. This can be used to provide justification for the systems selection and ranking decisions.

The system is designed to be adaptive by allowing the decision modelling phases 1 to 4 to be repeated over time as expert's preferences change or new experts are added to the system. This allows a progressive improvement of the systems ability to embed richer domain knowledge based on the different opinions, preferences and decision making behaviour of domain experts.

The transparency of the system allows its ranking decisions to be evaluated either automatically or interactively by end users. Recommendations can be fed back into the system to adjust its internal fuzzy decision models in order to improve ranking accuracy in the future.

V. EXPERIMENTS AND RESULTS

We have performed unique experiments in which our neuro-fuzzy approach for modelling group decisions has been used to capture the job role requirements preferences from a selection panel of five recruitment experts within the health and social care occupation domain. The system then recorded the ranking decisions made by each expert on a set of 40 applicant CVs based on their selected requirement preferences. Fuzzy sets were used to model the ranking decisions of each expert. These were weighted by a consistency coefficient derived from observing the ranking behaviour of each expert. The uncertainties within the experts' panel were modelled by combining the weighted fuzzy sets for each expert using the weighted sum group ranking decision procedure. Our system was evaluated based on the ranking decisions it produced for the 40 applicants CVs when compared with those produced by the human experts.

The job role for which the person specification had to be created was for a Qualified Nurse Care Home Manager, for a 90 bed care home with 80 Dementia and 10 mental health patients. The five domain experts in the selection panel comprised of: two recruitment managers, one senior recruitment manager, the managing director and the marketing director of a care agency. The five experts were each asked to select from a list of 87 occupation specific characteristics pertaining to a Care Home Manager. The characteristics were grouped into 10 sub groups pertaining to general and specific experiences, soft and technical skills, licenses, registration & checks, working knowledge, qualifications, training, years of management experience and the frequency of job changes within a five year period.

Each expert in the selection panel was asked to select characteristics based on their preferences. The '*Minimum'* required characteristics for the job role were predefined as a Criminal Record Bureau (CRB) check, Membership of the Commission for Social Care Inspectors (CSCI), and a Nursing Qualification. A person specification for the job role was therefore produced by each expert, which comprised his or his preferences for the requirement characteristics an applicant should possess.

Each of the five experts was then asked to rank 40 candidate CVs based on their selected characteristics. For each CV the skill attributes that matched the expert's requirements criteria were recorded along with the ranking decision that was taken. Each of the CVs was ranked into the three linguistic categories: '*Poor*', '*Moderate*' and '*Good*'. The neural network feature weighting method described in phase 3 was used to analyse the CV data collected from each expert. Based on the matching skills from the CVs and their ranking, the approach weighted the characteristics to determine the most important contributing skill attributes that characterised each ranking decision of the expert. The following training parameters were used for the neural network. The objective function for training was based on the root mean squared error of the desired and target outputs from the network. The maximum number of training epochs for the network was set to 5000 epochs with a training termination error of 0.010. The networks learning rate and momentum were set to: 0.05 and 0.9 respectively.

The weighted decision specific skills selected by the neural feature weighting method for each expert were used to generate the parameters for the right shoulder fuzzy sets associated with the linguistic labels for '*Poor*', '*Moderate*' and '*Good*' modelling the expert's ranking decisions, as explained in phase 4.

A consistency coefficient of each expert's ranking behaviour was determined as described in phase 4. The fuzzy sets produced for each expert were then weighted based on their derived consistency coefficient value.

The 40 applicant CVs were used to evaluate the performance of the system in its ability to produce ranking decisions that were consistent with the human experts. The skills attributes described in each CV were extracted and scored against the expert's preferences. The scores for each CV were then ranked based on a group ranking decision produced by mapping the scores to fuzzy sets produced for each expert's ranking decisions. The fuzzy membership values obtained from the ranking scores were aggregated together to derive a weighted sum group ranking decision for each CV as is described in phase 5.

For each CV, the aggregated group ranking decision of the system was compared to the manual ranking decisions of each of the five experts in the selection panel according to the same linguistic labels: *Poor*, *Moderate* and *Good* associated with the fuzzy sets generated by the system. To quantifiably evaluate the system's ranking decisions against those of the human experts we replaced the linguistic terms with numerical values such that the labels: *Poor*, *Moderate* and *Good* were replaced with the values *1*, *2* and *3* respectively. For each expert their numerical ranking decisions for the CVs were then weighted by their respective consistency coefficients to factor in the strength of their ranking opinions. A weighted group ranking decision was calculated for all the experts. Numerical decision bounds were decided for each linguistic decision and decisions that were calculated to be outside of these bounds would be classed as *borderline* decisions.

Table I shows the CV weighted ranking decisions of each of the five human experts and their group ranking decision, which is compared to the ranking decisions of our system. The linguistic group ranking decisions of the human experts and our system is also shown where linguistic labels: *Poor*, *Moderate* and *Good* are replaced with *P*, *M* and *G* respectively.

TABLE I
RANKING DECISIONS OF SYSTEM AND HUMAN EXPERTS

CV num	Individual experts weighted ranking decisions					Group ranking decision (linguistic and weighted)		System output decision (linguistic and weighted)	
	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5				
1	2.92	2.84	2.84	2.68	3.00	G	3.00	G	3
2	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
3	2.92	2.84	2.84	2.68	3.00	G	3.00	G	3
4	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
5	1.95	2.84	2.84	1.79	3.00	G	2.61	M	2
6	2.92	2.84	1.89	1.79	2.00	M	2.40	G	3
7	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
8	2.92	1.89	1.89	1.79	3.00	M	2.41	M	2
9	1.95	1.89	1.89	0.89	2.00	M	1.81	P	1
10	2.92	1.89	0.95	1.79	3.00	M	2.22	M	2
11	1.95	2.84	0.95	1.79	2.00	M	2.00	G	3
12	2.92	1.89	2.84	2.68	3.00	G	2.80	G	3
13	1.95	0.95	0.95	1.79	2.00	M	1.60	P	1
14	1.95	1.89	0.95	1.79	2.00	M	1.80	M	2
15	1.95	1.89	2.84	2.68	3.00	G	2.60	G	3
16	1.95	0.95	0.95	0.89	2.00	P	1.41	P	1
17	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
18	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
19	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
20	1.95	2.84	2.84	2.68	3.00	G	2.80	G	3
21	2.92	2.84	2.84	1.79	2.00	G	2.60	M	2
22	1.95	2.84	2.84	2.68	3.00	G	2.80	G	3
23	2.92	2.84	1.89	1.79	2.00	M	2.40	M	2
24	2.92	2.84	2.84	1.79	2.00	G	2.60	G	3
25	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
26	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
27	2.92	2.84	1.89	1.79	2.00	M	2.40	M	2
28	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
29	2.92	2.84	2.84	2.68	3.00	G	3.00	G	3
30	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
31	1.95	2.84	1.89	1.79	3.00	M	2.41	G	3
32	2.92	1.89	1.89	1.79	2.00	M	2.20	M	2
33	0.97	1.89	0.95	1.79	2.00	M	1.60	M	2
34	1.95	2.84	1.89	1.79	3.00	M	2.41	G	3
35	2.92	2.84	2.84	1.79	3.00	G	2.81	G	3
36	1.95	1.89	1.89	1.79	2.00	M	2.00	M	2
37	0.97	0.95	0.95	0.89	1.00	P	1.00	P	1
38	0.97	2.84	2.84	1.79	3.00	M	2.40	G	3
39	2.92	1.89	0.95	1.79	2.00	M	2.01	M	2
40	0.97	0.95	0.95	0.89	1.00	P	1.00	P	1
System ranking accuracy									82.8%

The system has been shown to mimic the collective human experts aggregated group weighted ranking decisions to an accuracy of 82.8%. The system is shown to be able model the unambiguous ranking decisions of the group of experts. The use of fuzzy sets also enables our system to represent the borderline decisions of the collective experts (shown as the shaded rows in Table I), due to their ability to represent partial fuzzy memberships between the different ranking decisions and their strengths. The system was therefore able to produce decisions that were relatively highly consistent with the human experts.

VI. CONCLUSIONS

In this paper, we presented a neuro-fuzzy based agent that enabled automating the processes of job requirements specification for applicant ranking in HR systems. The agent can capture the most important job requirements preferences from the panel of experts to generate a person specification that reflects the collective unbiased opinion of the experts in a consistent and objective way.

Neural networks were used to identify the key skill attributes and their weights, providing an automatic method for charactering the experts ranking decisions. Fuzzy sets were used to model the uncertainties arising due to the varying preferences of each expert in a selection panel. The consistency of each expert's decisions are determined and used to weight his or her contributions to the group decisions making process. A scoring method was used to score the applicant CVs based on how closely they match the requirements preferences of the experts. The scores are mapped to the fuzzy sets, which are weighted based on the calculated experts' consistencies, and aggregated to determine a linguistic ranking for the CVs.

The paper has presented experiments in which the system has elicited requirement preferences from a selection panel of five recruitment experts within the residential care sector. Our system was able model their collective ranking decisions, which was evaluated on a set of forty applicant CVs. The system was able to show the strengths of its ranking decisions and which ranking decisions were borderline due to the diverging opinions of the experts. The system produces linguistic ranking decisions that 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 plan to integrate the developed system with information extraction and parsing systems to facilitate the capture of the applicants' skills from unstructured CVs. Our approach currently uses type-1 fuzzy sets and we plan to extend this to use adaptive type-2 fuzzy sets to model higher degrees of uncertainties associated with group decision making and consensus modelling.

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