A fuzzy expert system (FES) tool for online personnel recruitments

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Abstract: The advent of the internet has facilitated greater access to the myriad of job opportunities available globally. Currently there exist many job application submission portals that are being used for online job recruitment purposes. However, the task of many of these job submission portals is limited to matching the professional and academic qualifications of applicants with the requirements of employers and several organisations and does not involve the ranking of applicants' credentials according to their relative suitability for the jobs applied for. In this paper, we describe the implementation of fuzzy expert system (FES) tool for selection of qualified job applicants with the aim of minimising the rigour and subjectivity associated with the candidate selection process. A performance evaluation of the FES tool that was conducted confirmed the viability of a FES-based approach in handling the fuzziness that is associated with the problem of personnel recruitment.

Keywords: online job recruitment; fuzzy logic; fuzzy expert systems; FES; personnel selection; performance evaluation; job application portal; human resource management; HRM; organisation.

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1 Introduction

One of the opportunities provided by the internet is the opening up of the global job space through the increasing prominence of online job advertisement portals. This has greatly enhanced access of prospective job seekers to opportunities beyond national or continental boundaries. Also, it has provided greater opportunities for employers to recruit the most ideal candidates from a larger pool of applicants. This mode of online recruitment is becoming more popular not just because of its obvious advantages, in terms of cost reduction and increased visibility, but also because of the need to source for the most qualified candidates irrespective of sentiments. The eligibility criteria in most standard organisations are that candidates must

1 have a referee that introduces them
2 satisfy the minimum job requirements
3 possess other related qualities that can give them some kind of advantage (Werner, 2000).

Today, there exist many job application submission portals such as job.com, alljobsearch.com, job-hunt.org, carebuilder.com and many more, where job seekers can submit their resume. Many of these portals have the capability to match the professional and academic qualifications of job applicants with the requirements of existing job vacancies in the available job databases. These job databases are created by aggregating the several job vacancies harvested from the submissions of many corporate organisations that have affiliations with the job submission portal for the purpose of recruitment. However, the functionality of many of the existing online job submission portals does not include the ranking of applicants' credentials in order to determine their relative suitability for the jobs applied for (viz. they are 'dumb' job portals). This implies that these 'dumb' job portals lack the capability to alleviate the rigour and inherent subjectivity that is usually associated with the process of personnel selection.

Personnel selection approaches so far reported in literature can be broadly classified into two categories: the analytic hierarchy process (AHP) approaches and the artificial intelligence approaches. The AHP makes use of a multi-hierarchical structure that is based on the theory of constructing hierarchies, setting priorities, and reasonable consistency (Saaty, 1995). The AHP is a powerful and flexible decision-making process to assist people set priorities and make the best decision when both qualitative and quantitative aspects of a decision need to be considered. The work of Liu and Shih (2005), and Scholl et al. (2005) are among the recent examples of AHP approaches. On the other hand, artificial intelligence approaches embrace the use of techniques such as: expert systems (Mehrabad and Brojeny, 2007); fuzzy expert system (FES) (Golec and Kahya, 2007; Canós and Liern, 2008; Canós and Liern, 2004); data mining (Chien and Chen, 2008; Wei-Shen and Chung-Chian Hsu, 2006); rough set (Chien and Chen, 2007); artificial neural networks (Drigas et al., 2004; Huang et al., 2006) for personnel selection.

However, none of the efforts earlier reported in literature has been applied specifically to solve the problem of ‘dumb’ job application portals, such that they become enabled for relevance in the actual candidate selection process. In this work, a FES approach that can enable existing job application portals with personnel selection capability in a way that minimises subjectivity is presented.

The issue of subjectivity can have a negative effect on the quality of a selection process if not properly controlled. This is particularly true in instances when the personal sentiments of the decision-maker come into play. Some of the real life instances that can ordinarily warrant subjective judgments include:

1 instances when the core competency needed by an organisation is not directly available in the database and there is the need to choose subjectively from candidates in closely related discipline

2 instances when two or more candidates have the same or almost similar qualifications

3 instances when the assessment parameters being used are fuzzy, inexact and qualitative (e.g. excellent, very good, good, fair, bad).

Fuzzy reasoning is a model of human intelligence that can be introduced into computer systems using the mathematical concept of fuzzy logic. It empowers a system to be able to handle instances of approximate reasoning and fuzziness just like humans will do. Therefore, as a solution approach to the problem of fuzziness in the candidate selection process, we present in this paper, the design and implementation of FES that is capable of initiating intelligent decision making in the ranking and evaluation of the credentials of job candidates. To do this, the FES uses a set of objective parameters relative to specific job requirements to evaluate the relative suitability of the job candidates for the specific job vacancy concerned in way that minimises subjectivity.

The rest of this paper is structured as follows. In Section 2, is a report of some related work, while an overview of relevant fuzzy logic concepts is given in Section 3. Section 4 presents an illustration of the personnel selection problem, while in Section 5, we give a detailed description of the design and implementation methodology of the FES, and the procedure adopted for its evaluation. The paper is concluded in Section 6 with a brief note.

2 Related work

Recruitment is an important issue of human resource management (HRM). The main purpose of recruitment is to engage the best available talents from within or outside the organisation for available job positions. A number of AI-based approaches in the area of personnel selection have been reported in literature which is our bias in this paper. Wei-Shen and Chung-Chian (2006), proposed a personnel selection tool based on fuzzy data mining method to assist business managers to find eligible talent more efficiently. In the work, a fuzzy data mining method was applied to discover those predictors or attributes which are valid to predict the organisational behaviour of applicants in the future. This was done in contrast to the traditional personnel selection methods such as personality, interview, assessment centre, and biodata that were until then usually engaged in businesses. The fuzzy data mining method was applied to obtain valid fuzzy association rules from existing transaction database using the Apriori algorithm. An experiment was implemented in a real case to validate the method proposed. The important contribution of this work is that it goes beyond personnel selection to predicting the future organisational behaviour of employees.

Chien and Chen (2008) posited that human capital is one of the core competences for high-tech companies to maintain their competitive advantages in the knowledge economy, and that personnel recruitment and selection directly affect the quality of employees. In their research, decision tree analysis was employed to discover latent knowledge and extract the rules to assist in personnel selection decisions in a high-tech company. Furthermore, using the information gathered, domain experts from the company can also generate recruiting and HRM strategies. Specifically, a framework for human resource data mining was constructed to explore the relationships between personnel profiles and work behaviours. The Chi-squared automatic interaction detection (CHAID) algorithm was used as the data mining tool to explore the latent relationships among the input employee profiles and target variables of work behaviours such as job performance, retention, and turnover reasons. Their approach is one of the rare applications of data mining approaches for personnel selection so far reported in literature. Also, the work of Ranjan et al. (2008) outlines the role of data mining in HRM systems (HRMS) and shows how data mining can be used to discover new knowledge and extracts useful patterns from large data set for HR decision making. The work clearly demonstrates the ability of data mining to improve the quality of the decision-making process in HRMS and gives propositions regarding whether data-mining capabilities should lead to increased performance to sustain competitive advantage.

There exist other instances in literature where fuzzy logic and fuzzy expect systems have been employed for personnel selection. Petrovic-Lazarevic (2001) presents a two-level employee personnel selection fuzzy model for short listing and hiring decision in order to minimise subjective judgment associated with the process of filling vacant job positions. The model used consists of an AHP of three levels. The first level involves the preliminary selection of candidates and the identification of the main decision factors which are represented as fuzzy linguistic variables (LVs) to revise multi-objective models of decision-making. The values of the variables are calculated as expected values of the fuzzy variables. The second level entails the process of selecting a final candidate for a job position. Here, the personal expectations of each employee are used as the basis to evaluate their fitness for the job, while the third level assesses the utility of engaging the appropriate employee. The work attempted to minimise subjectivity in the process of distinguishing between an appropriate employee and an inappropriate employee for a job vacancy using multi-objective models of decision making. Golec and Kahya (2007) opined that the employee evaluation and selection system is an important problem that can significantly affect the future competitiveness and the performance of an organisation. In their work, a comprehensive hierarchical structure for selecting and evaluating a right employee for a job was presented. The structure used allow to systematically build the goals of employee selection process, identify the suitable factor and measure indicators, and set up a consistent evaluation standard for facilitating a decision process. A competency-based fuzzy model was used to match an employee with a specific job requirement. An example was used to demonstrate the feasibility of the approach canvassed. As a contribution, the approach signifies a capable way to accommodate the imprecision, qualitative factors inherent in attempting to validate employee selection based on competency at the strategic level in an organisation.

In Canós and Liern (2004), some fuzzy logic models for decision-making in HRM issues like personnel selection and optimal staff design were implemented. The flexibility of the models built allows for the ranking of the applicants for a job by using distance measures (Hamming distance) or similarity degrees with an 'ideal candidate'. In cases, where an external valuation is available, the ordered weighted averaging (OWA) aggregation operators was used to assign different weights to selection criteria in order to imitate human expert valuation. In instances of merger or acquisition when the staff design is more complicated two fuzzy linear programming methods were proposed to make viable mathematical model for decision making in such instances. The fuzzy models were implemented in MS EXCEL to demonstrate the simplicity of their implementation. Also, Canós and Liern (2006) reported the development of a flexible decision support system (DSS) to help managers in their decision-making functions. The DSS simulates experts' evaluations using OWA aggregation operators, which assign different weights to different selection criteria. An aggregation model based on efficiency analysis was used to rank the candidates into an order. This is premised on their belief that the main goal of managers is to obtain a ranking of a set of candidates who have been evaluated according to different competences. Therefore, the development of efficient and flexible information aggregation methods is a main issue in information access methods.

The main point of difference of our work compared to these earlier approaches is that our effort is primarily addressed to solve the problem of 'dumb' job application portals, such that they become enabled for relevance in the actual candidate selection process. Hence this work offers as its contribution a case study of the application of FES approach in furthering the capabilities of existing online job application portals.

3 Overview fuzzy logic

Fuzzy logic is a mathematical technique for dealing with imprecise data (attribute) and problems that have many solutions or values rather than one. The concept was conceived by Zadeh in 1965 (Zadeh, 1965, 1975). It represents knowledge based on the degree of membership. It is a theory of fuzzy sets, the set that calibrates vagueness and provides an approach to approximate reasoning in which the rules of inference are approximate rather than exact. Fuzzy set theory provides a systematic calculus to deal with information linguistically and perform numerical computation by using linguistic labels stipulated by membership function (MF).

A fuzzy set A in a universe of discourse X is characterised by MF which associates with each element x in X ($x \in X$) a real number in the interval [0, 1], which indicates the extent to which x belongs to the fuzzy set X (Xu et al., 2005). A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal. Fuzzy set is different from classical set in the sense that while a classical set considered its elements based of Boolean logic; that is an element is either a member or not (1 or 0), fuzzy set considers all its elements based on fuzzy logic (viz. it considers every element based on their degree of membership in X) (Schneider et al., 1996). The definitions of some core fuzzy logic concepts that are relevant to the context of this paper are given as follows:

Definition 1: A LV is a variable whose values are expressed in linguistic terms. In other words variables whose values are not numbers but words in a natural or artificial language [3]. For example 'class of degree' is a LV whose values are 1st class, 2–1 (second class upper division), 2–2 (second class lower division), 3rd class and pass.

Definition 2: The MF μ_A (x) can be defined as the membership of the elements x of the base set X in the fuzzy set A. The grade of membership μ_A (x_o) of a MF μ_A (x) describes to which grade, the special element $x = x_o$ belong to the fuzzy set A. The MF maps the elements of the universe on to numerical values in the interval [0,1]. A fuzzy set A is a set of ordered pairs:

$$A = ((x, \mu_A(x)) : X \to [0,1], \ x \in X, \mu_A(\text{x}) \in [0,1].$$

$$\begin{array}{ll} \mu A(x) = 1 & \text{if } x \text{ is totally in } A \\ \mu A(x) = 0 & \text{if } x \text{ is not in } A \\ 0 < \mu A(x) < 1 & \text{if } x \text{ is partly in } A. \end{array}$$

Definition 3: Assume A is a fuzzy subset of X, the support of a fuzzy set A is the set of all points x in X such that $\mu_{A(x)} > 0$:

$$Support(A) = \{x | \mu A(x) > 0 \text{ and } x \in X\}$$

Definition 4: The core of a fuzzy set A is the set of all point x in X such that $\mu_{A(x)} = 1$:

$$core(A) = \{x | \mu A(x) = 1 \text{ and } x \in X\}$$

3.1 MF formulation and parameterisation

A fuzzy set is completely characterised by its MF, and as such the classes of parameterised functions commonly used to define MFs of one dimension are: triangular MF, trapezoidal MF, Gaussian MF, generalised bell MF (Padhy, 2005)

a *Triangular MFs:* This is specified by three parameters (a, b, c) where ($a < b < c$). It can be represented in either of the following:

$$triangle(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right) \quad \text{(i)}$$

$$triangle(x; a, b, c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \quad \text{(ii)}$$

b *Trapezoidal MFs:* This is specified by four parameters {a, b, c, d} where ($a < b <= c < d$). It can be represented in either of the following:

$$trapezoid\ \ (x; a, b, c, d = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c} \right), 0 \right) \quad \text{(i)}$$

$$trapezoid(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases} \quad \text{(ii)}$$

c *Gaussian MF:* A Gaussian MF is specified by two parameters $\{c, \sigma\}$; c represents the MF's centre and σ determines the MF's width.

$$gaussian(x;c,\sigma) = \exp\left(\frac{-(x-c)^2/\sigma^2}{2}\right)$$

d *Generalised bell MFs:* A generalised bell MF or simply called bell MF is specified by three parameters $\{a, b, c\}$:

$$bell(x;a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}}$$

where parameters a, and c represents the width and the MF's centre respectively while b represents the slope of the crossover point, and it is usually positive (if b is negative, the shape of this MF becomes an upside-down bell).

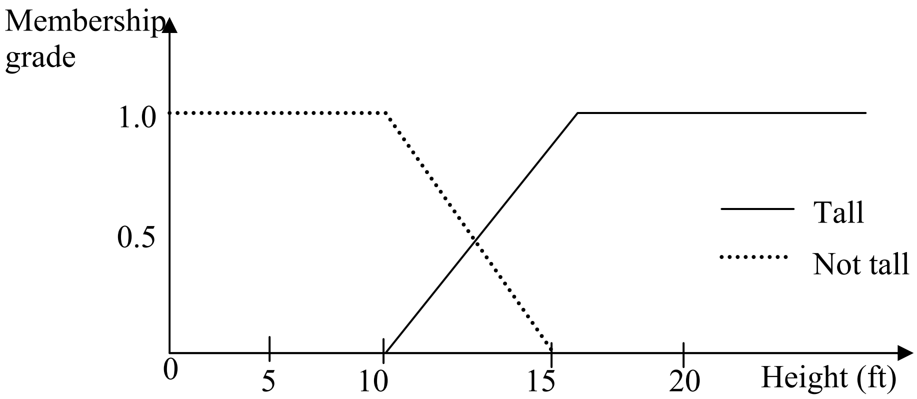
3.2 Basic operations in fuzzy logic

The basic operations that could be performed on fuzzy sets include:

3.2.1 Compliment

This shows to what extent an element does not belong to the set. For example, if we have the set of tall men, its complement is the set of NOT tall men. The membership representation is shown in Figure 1.

Figure 1 Compliment of fuzzy set



If *A* is the fuzzy set, in a universe *X*. Its complement *A* can be found as follows:

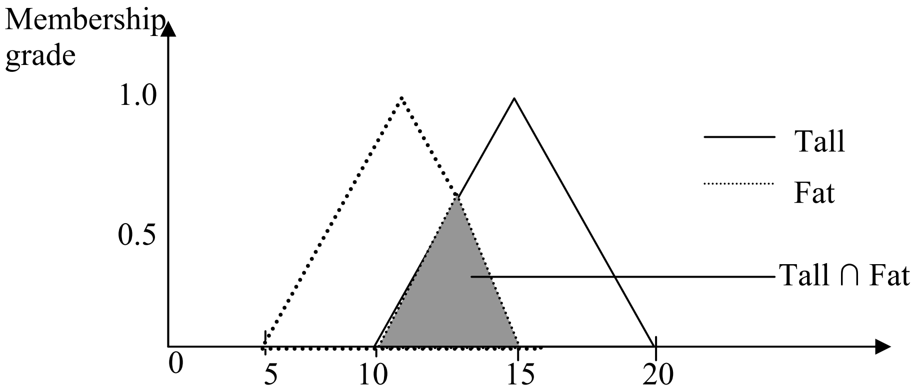
$$\mu A(x) = 1 - \mu A(x) \text{ for all } x \in X$$

3.2.2 Intersection

This shows the extent to which an element is in both sets (see Figure 2). For example, the intersection of the set of tall men and the set of fat men is the area where these sets overlap. A fuzzy intersection is the lower membership in both sets of each element. The fuzzy intersection of two fuzzy sets *A* and *B* on universe of discourse *X*:

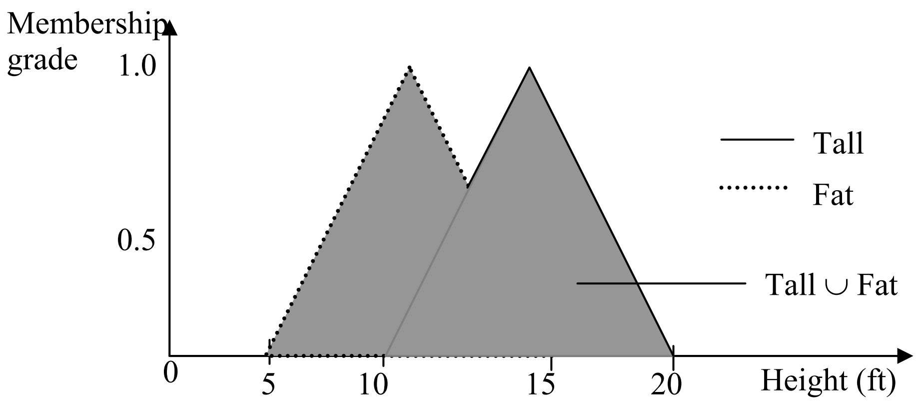
$$\mu A \cap B(x) = \min[\mu A(x), \mu B(x)] = \mu A(x) \cap \mu B(x), \text{ for all } x \in X$$

Figure 2 Intersection of fuzzy sets



3.2.3 Union

Figure 3 Union of fuzzy sets



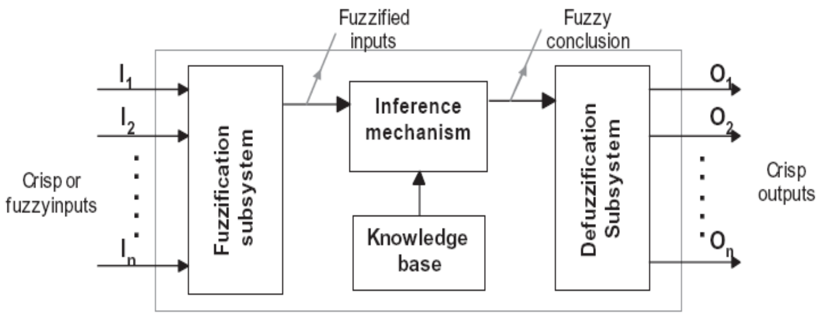
This shows how much of the element is in either set. In fuzzy sets, the union is the reverse of the intersection. That is, the union is the largest membership value of the element in either set (see Figure 3). For example, the union of tall men and fat men contains all men who are tall OR fat. The fuzzy operation for forming the union of two fuzzy sets *A* and *B* on universe *X* can be given as:

$$\mu A \cup B(x) = \max[\mu A(x), \mu B(x)] = \mu A(x) \cup \mu B(x), \text{ for all } x \in X$$

3.3 Fuzzy expert system

A FES is an expert system that employs the concepts of fuzzy logic instead of the Boolean logic to reason about data as its inference mechanism (Aly and Vrana, 2006). It consists of fuzzification, inference, knowledge base, and defuzzification subsystems, and uses a collection of fuzzy MFs and fuzzy rules. It has the capability to solve decision making problems for which no exact algorithm exists by relying on human-like models of approximate reasoning that are expressed in form of fuzzy IF-THEN rules. FESs are well suited to problems that exhibit uncertainty resulting from inexactness, vagueness or subjectivity. The structure of a FES is illustrated in Figure 4.

Figure 4 Standard FES architecture



Source: Kosko (1992)

3.3.1 Fuzzy inference system

This is a popular computing framework based on the concept of fuzzy set theory, fuzzy IF-THEN rules and fuzzy reasoning. The fuzzy inference engine is responsible for the evaluation of fuzzy rules to produce an output for each rule (Wang and Mendel, 1995; Padhy, 2005).

The basic structure of fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules. A database (or dictionary), which defines the MFs used in the fuzzy rules; and a reasoning mechanism, which perform the inference procedure upon the rules, and the given facts, to derive a reasonable output or conclusion.

A fuzzy inference system can take either fuzzy inputs or crisp inputs but its outputs are almost always fuzzy sets. Sometimes it is necessary to have a crisp output, especially in a situation where a fuzzy inference system is used as a controller. In such cases a method of defuzzification is needed to extract a crisp value that best represents a fuzzy set. The three most popular fuzzy inference systems are the: Mamdani fuzzy model, Tagaki-Sugeno fuzzy model, and Tsukamoto model. The FES tool for personnel recruitment that is implemented in this work is based on the Mamdani fuzzy model.

3.3.2 Mamdani fuzzy inference

The Mamdani-style fuzzy inference process is performed in four steps:

1. fuzzification: this involves definition of fuzzy sets, and determination of the degree of membership of crisp inputs in appropriate fuzzy sets
2. inference: this involves evaluation of fuzzy rules to produce an output for each rule
3. composition: this entails aggregation or combination of the outputs of all rules
4. defuzzification: this involves computation of crisp output.

4 An illustration of the recruitment problem

In order to demonstrate the relevance and the applicability of the FES for personnel recruitment, an illustration of the recruitment problem scenario is presented as follows:

Suppose an organisation wishes to secure a candidate for a particular job position and desires to analyse and evaluate the resume of various candidates submitted online in respect of the specific job advertised (note that since the focus is online submission, there are some factors that may not be considered since personal interaction with each candidate might not be possible, however, considerably crucial information can be collected through the resume which can be a basis for evaluation). Given that the required qualifications and other desirable factors are clearly stated, or stated imprecisely such as: Qualification, class of degree, years of experience (YOE), certifications, age, course of study (COS) etc. We assume that the post of a system engineer is considered to be vacant and needed to be filled with the requirements stated as follows in Table 1.

Table 1 Requirements for system engineer

S/no	*Requirements parameters*	*Fuzzy values*
1	Qualification	MSc or equivalent
2	Class of degree	Second class lower (2–2) (minimum)
3	YOE	Not less than five years and not more than ten years
4	Certification	Professional certification (offers advantage)
5	Age	Within the age range of 25–30
6	COS	Computer engineering or related discipline

If the permissible range of input values for candidate per requirement is given as follows:

qualification

1. BSc*/HND*/0.8
2. BSc'/HND' + PGD*/0.4
3. MSc*/1.0
4. MSc' + PGD*/0.6

5 PhD*/0.4

where * connotes that degree is in computer engineering and ’ connotes that degree is not in computer engineering but in a related discipline

class of degree $2.4 < x <= 5.0$ (for a maximum of 5.0 grade point average)

YOE $4 < x <= 10$

certification yes/no (1 or 0)

age $25 <= x <= 30$

COS

1 computer engineering/1
2 electrical/electronics/1
3 computer science + PGD (comp eng)/0.8
4 physics (electronics)/0.8
5 computer science/0.6
6 any other engineering courses + PGD (comp eng)/0.4.

4.1 Solution approach

In solving this example problem, the different types of qualifications and COS, have been assigned fuzzy values in the interval [0, 1] based on their relative closeness to the specific job requirement. In this specific case, computer engineering and electrical engineering have the value 1.0 because they perfectly match the COS requirement for the ‘ideal’ candidate for the system engineer position, hence the values are used as direct fuzzy number inputs. Also, other real valued LVs that are part of the requirement parameters are assigned appropriate membership values by fuzzification once the fuzzy set for that parameter has been defined.

As an example, the case of two candidates that have applied for the post of system engineer with differing credentials is shown in Table 2.

Table 2 Credentials of candidates

S/no.	*Qualification*	*Class of degree/ cumm. grade point*	*YOE*	*Professional certification*	*Age*	*COS*
1	BSc	2–2 (3.7)	5	Yes	26	Computer engineering
2	HND + PGD	2–2 (2.95)	6	Yes	29	Computer science

The fuzzy set representation for the 6 basic requirements is given as:

qualification (BSc*/HND*)/0.8 + (BSc’/HND’, PGD*)/0.4 + (MSc*)/1 + (MSc’ + PGD*)/0.6 + (PhD*)/0.4

class of degree $2.49/0 + y = -0.99 + x/2.51 + 5.00/1$ (using the linear MF)

YOE $4/0 + y = -0.67 + x/6 + 10/1$

certification yes/1 + no/0

age 25/0 + 26/0.33 +27/0.67 +28/1 + 29/0.5 + 30/0 (using triangular MF).

Then, the membership values for the requirement parameters of the first and second candidates are given as:

$$C1 = 1/0.80 + 2/0.48 + 3/0.16 + 4/1.00 + 5/0.33 + 6/1.0$$

$$C2 = 1/0.40 + 2/0.18 + 3/0.30 + 4/1.00 + 5/0.50 + 6/0.60$$

The fuzzy hamming distance measure for the two candidates under consideration using all six parameters is shown in Table 3.

Table 3 Fuzzy distance measure for candidate ranking

	$\left|\mu_O(x_i) - \mu_R(x_i)\right|$	
Parameters	*C1*	*C2*
Qualification	0.2	0.6
Class of degree	0.52	0.82
YOE	0.84	0.7
Certification	0.0	0.00
Age	0.67	0.5
COS	0.0	0.4
$\delta(O,R) = \sum_{i=1}^{n} \left|\mu_O(x_i) - \mu_R(x_i)\right|$	2.23	3.0

Based on the result obtained, it can be concluded that the first candidate (C1) is closer to the requirement for the job of system engineer than second candidate (C2). Hence C1 is ranked higher than C2 in the order of job consideration. The solution approach demonstrated in this example is the one emulated by the FES tool for job recruitment that is presented in this paper.

5 Description of architecture of FES tool

The architecture of the FES tool (see Figure 5) consists of following:

1 *System input:* This consist of the candidates' profile database, and the job vacancy database. The candidates' profile database contains information that pertains to individual candidates as obtained from the candidate profile form filled by each candidate online. It provides the pool of information on job-seeking candidates that are subsequently evaluated for job placements. The candidates' profile database grows continually as more candidates subscribe to the FES. The job vacancy database is the other input into the FES which contains the specific employment requirements which a prospective job seeker must fulfil in order to qualify for consideration for the available jobs.

2 *The fuzzy inference system:* This is the fuzzy logic engine of the FES which consists of:

- *A fuzzifier component:* This handles the conversion of input values obtained from candidates' profile into fuzzy values within requirements parameter fuzzy set.
- *A fuzzy rule base:* This contains the set of fuzzy IF-THEN rules that embodies the knowledge used by the fuzzy inference system. It represents the knowledge base of the expert system. Each of the rules has an antecedent (IF) and a conclusion (THEN) part that prescribes what should be done when certain conditions are true. The specific criteria for selection for each specific job position are represented as IF-THEN rules which determine the eligibility of candidates.
- *A fuzzy inference engine:* This implements the fuzzy reasoning of the FES by combining the fuzzified inputs with the fuzzy rules using the Mamdani-style fuzzy inference process.

3 *Candidate ranking components:* This computationally evaluates the closeness of each candidate's fuzzified credentials to the ideal requirements for a specific job using the fuzzy hamming distance function. This fuzzy distance metric is used to rank candidates' profile in the order of their eligibility for the job. The fuzzy hamming distance is given as (Padhy, 2005):

$$\delta(O,R)=\sum_{i=1}^{n}\left|\mu_O(x_i)-\mu_R(x_i)\right|$$

where

$\mu_O(x_i)=1$ if x is totally in O

$0<\mu_R(x_i)<1$ if x is partly in R for each parameter included in a specific job requirement.

4 *Decision and result interface:* This is a logic component that ensures that only candidates that score above the pre-determined minimum cut-off for a particular job vacancy are recommended. It also has a GUI interface that displays the final result.

Figure 5 Conceptual view of FES for candidate selection

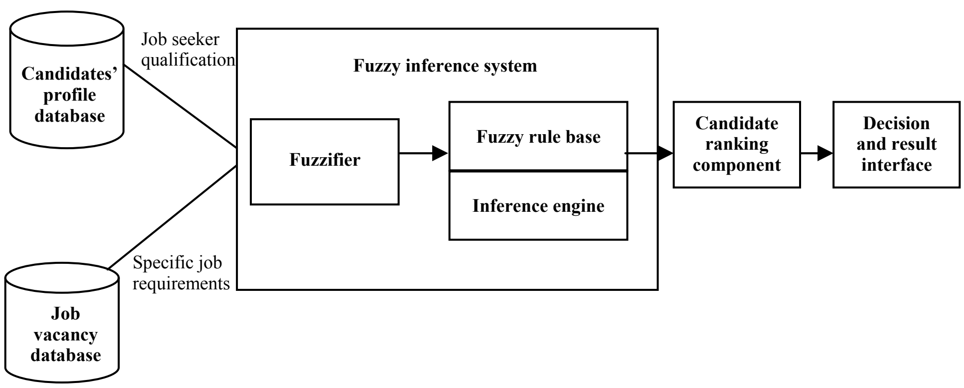


Figure 6 FES interface showing fuzzified values from candidate credentials (see online version for colours)

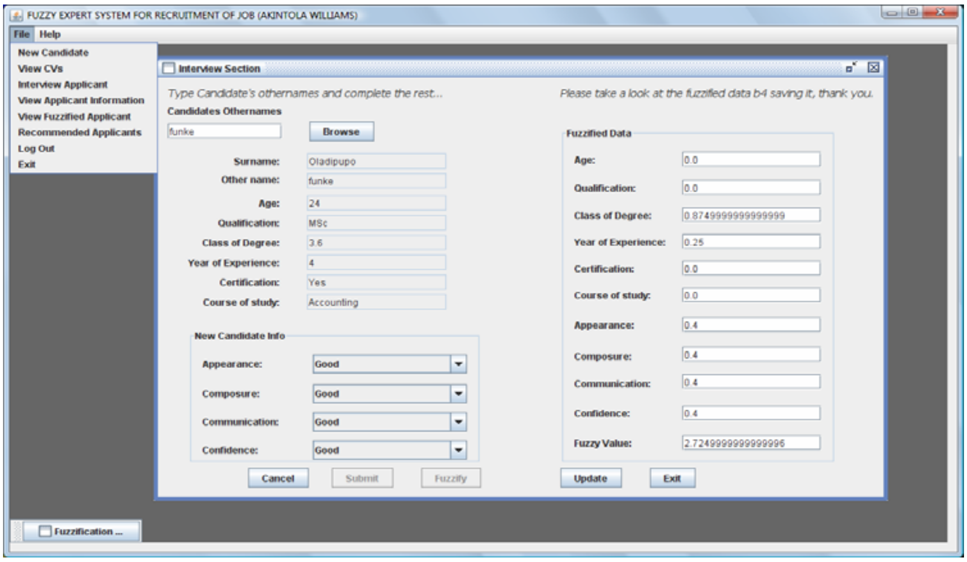
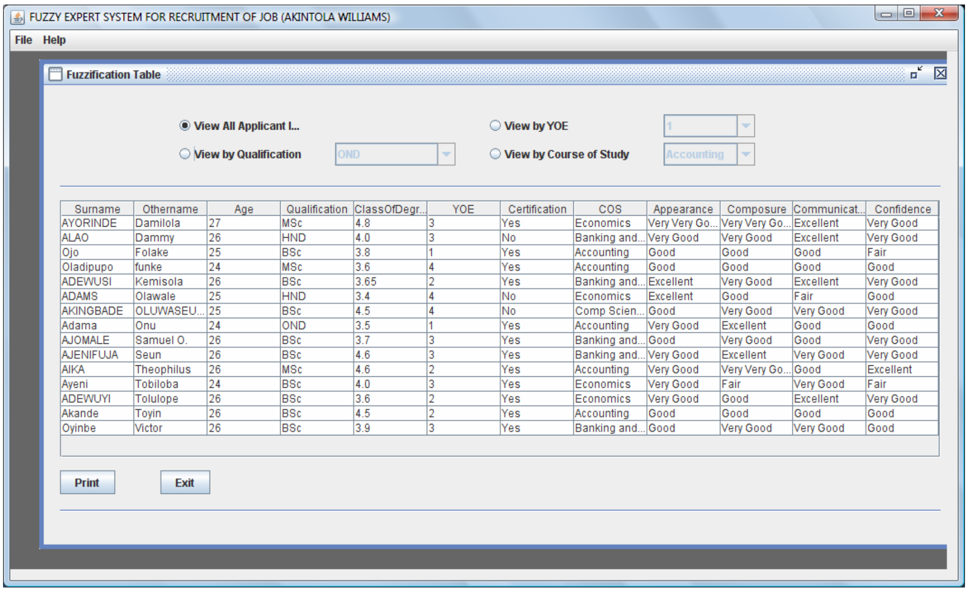


Figure 7 FES interface showing data captured from candidates (see online version for colours)



Surname	Othername	Age	Qualification	ClassOfDegr...	YOE	Certification	COS	Appearance	Composure	Communicat...	Confidence
AYORINDE	Damilola	27	MSc	4.8	3	Yes	Economics	Very Very Go...	Very Very Go...	Excellent	Very Good
ALAO	Dammy	26	HND	4.0	3	No	Banking and...	Very Good	Very Good	Excellent	Very Good
Ojo	Folake	25	BSc	3.8	1	Yes	Accounting	Good	Good	Good	Fair
Oladipupo	funke	24	MSc	3.6	4	Yes	Accounting	Good	Good	Good	Good
ADEWUSI	Kemisola	26	BSc	3.65	2	Yes	Banking and...	Excellent	Very Good	Excellent	Very Good
ADAMS	Olawale	25	HND	3.4	4	No	Economics	Excellent	Good	Fair	Good
AKINGBADE	OLUWASEU...	25	BSc	4.5	4	No	Comp Scien...	Good	Very Good	Very Good	Very Good
Adama	Onu	24	OND	3.5	1	Yes	Accounting	Very Good	Excellent	Good	Good
AJOMALE	Samuel O.	26	BSc	3.7	3	Yes	Banking and...	Good	Very Good	Good	Very Good
AJENIFUJA	Seun	26	BSc	4.6	3	Yes	Banking and...	Very Good	Excellent	Very Good	Very Good
AIKA	Theophilus	26	MSc	4.6	2	Yes	Accounting	Very Good	Very Very Go...	Good	Excellent
Ayeni	Tobiloba	24	BSc	4.0	3	Yes	Economics	Very Good	Fair	Very Good	Fair
ADEWUYI	Tolulope	26	BSc	3.6	2	Yes	Economics	Very Good	Good	Excellent	Very Good
Akande	Toyin	26	BSc	4.5	2	Yes	Accounting	Good	Good	Good	Good
Oyinbe	Victor	26	BSc	3.9	3	Yes	Banking and...	Good	Very Good	Very Good	Good

5.1 Implementation details

The implementation of the FES tool was based on Java servlet technology, running on Sun Application Web Server 9.0 using the NetBeans 5.5.1 Java application development environment. The web interface for application submission was implemented using macro media flash and dream weaver web design tools, and Java server pages (JSP). The candidate profile database and job vacancy database were implemented as data tables with MySQL using the JDBC connector as the middleware for client-database connectivity. The MATLAB Builder JA 2.02 (www.mathworks.com/products/javabuilder) which allows functional modules that are developed using MATLAB to be automatically packaged as classes was used to build and wrap the fuzzy logic components of the FES (fuzzifier, fuzzy inference engine, fuzzy rule base) in Java codes so that they could be referenced as a standard Java classes. Figures 6 and 7 are snapshots from our implementation.

5.2 Performance evaluation of FES tool

Evaluation is the process of determining the appropriateness of a specific system relative to its functional requirements and objectives. Validation of an expert system is conducted by determining whether the system's outcome is consistent with the conclusions of the human experts. Validation focuses on evaluating the outcomes rather than the process by which the outcomes are determined. In our specific case, the output of the FES tool was validated by using a direct method following the approach of Salim et al. (2002).

The direct method of expert system validation is a quantitative assessment that requires the human expert to obtain a copy of the software to be evaluated and to perform a simple benchmark problem on the software. Based on past experience, the human expert answers a set of 14 questions about the software. The questions are quantitative and are based on a 0 (very false) to 5 (very true) numerical scales. After some arithmetic manipulation of these numbers, a single numerical factor results called the 'satisfaction level' that ranges from 0 (least satisfied user) to 5 (most satisfied user) is used to rank the expert system software in terms of its likelihood to satisfy a prospective end user.

5.2.1 Description of the evaluation experiment

In conducting a validation test on the FES with the primary aim of determining the users' satisfaction level, a small experiment to test the system's conclusions against those of human experts was conducted using the direct method. Ten human resource experts from Akintola Williams group (a leading human-resource management firm in Nigeria) were asked to participate in the survey. Each received an identical set of questionnaire alongside a copy of FES software. We installed the MATLAB component runtime (MCR) library on each of the target machine to ensure that the embedded MATLAB files in the FES function normally. The MCR consist of the full set of shared libraries required for executing MATLAB based components and provides complete support for all features of the MATLAB language and its toolboxes. The human experts were asked to give a rating of 0 to 5 of their assessment of the performance of the FES tool covering seven aspects and a total of fourteen questions. Table 4 shows a sample of a filled FES questionnaire test instrument and a typical computation of satisfaction score for one evaluator.

Table 4 A typical FES tool evaluation report

	Question	*Assessment value (0–5)*	*Weight*	*Value X weight*
	Correctness of answer			
1	Is there enough information to evaluate the FES tool?	4	(2)	8
2	Does the FES tool reach the same conclusion similar to that of a human expert?	5	(2)	10
3	Does the FES tool provide the right answer for the right reasons?	5	(2)	10
	Accuracy of answer			
4	Is the FES tool accurate in its answer(s)?	5	(2)	10
5	Is the answer complete? Does the user need to do additional work to get a usable result?	4	(2)	8
	Correctness of reasoning technique			
6	Does the answer change if new but irrelevant data is entered into the FES tool?	5	(1)	5
7	Does the system require a lot of irrelevant question to reach its answer?	0	(1)	0
	Sensitivity			
8	Does the answer change if irrelevant changes are made to the system rules?	5	(1)	5
	Reliability			
9	Does the FES tool crash or hang up in its host computer?	2	(1)	2
10	Does the system give warnings for instances of incomplete data or rules?	5	(1)	5
	Confidence			
11	Is one comfortable using the FES tool?	4	(1)	4
12	Does the conclusion of the FES tool give adequate satisfaction?	4	(2)	8
	Limitations			
13	Can limitations of the FES tool be detected at this point in time?	4	(1)	4
14	Can the FES tool learn from increased data or experience?	2	(1)	2
	Result $= \sum(\text{weight } x \text{ value}) / \sum(\text{weight})$		20	81
			4.05	

The weighting factors used for the computation of the satisfaction score in the experiment was based on the mutually agreed values that were established by the human expert evaluators that participated in the experiment.

At the end of our experiment, the mean satisfaction level as computed from the performance evaluation of the ten human expert evaluators was 3.9 out of the possible maximum score of 5.0, which is indicative a good performance (see Table 5).

Table 5 Result of evaluation experiment

Evaluator	*Computed satisfaction level*
1	4.05
2	4.16
3	4.21
4	3.52
5	3.84
6	4.22
7	4.21
8	3.89
9	4.2
10	3.57
Mean satisfaction level	3.987

6 Conclusions

In this paper, in contrast to many previous approaches, an attempt has been made to enable online job application portals with intelligent capability in order to make them more relevant in the actual process of candidate selection. Specifically, a FES tool was implemented to address the subjectivity and fuzziness associated with the manual process of human resource recruitment. The feasibility of a FES approach was demonstrated using a specific case study. An evaluation of the FES tool that was undertaken yielded satisfactory result to confirm the viability of a FES approach to enhancing the existing capabilities of many online recruitment systems. In future work, the possibility of engaging hybrid intelligent models for candidate selection process, and future personnel behaviour prediction would be explored. We will be looking to leverage the combination of fuzzy logic, rough set and some instance-base learning approach such as artificial neural networks and case-based reasoning.

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