A Fuzzy Inference System Approach to Resource Capability Assessment

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Abstract

The capability of a resource is an important aspect to consider in resource management and production planning. This paper extends on the system introduced in our previous work [3, 4] and outlines a resource capability assessment function to determine how well a worker's current capability matches up to that required by his or her job-role. The proposed function can also be used for the purpose of personnel selection in employment and promotion decisions. A fuzzy inference system approach is proposed for the development of the capability assessment function and a case study is carried out in industry to demonstrate the successful implementation and performance of the assessment method.

Keywords*: Human Resource, Capability Assessment, Fuzzy Inference System.*

1 Introduction

Dual resource constrained (DRC) systems are those that are constrained by both human and machine type resources [1, 2]. DRC systems are prevalent in real life industries and accurate assessment of the different characteristics presented by each type of resource is necessary to achieve effective resource management and utilization. In our previous work [3], the CERES system was introduced as an overall framework for resource management and production planning. The resource capability evaluation module is a sub-system of the bigger framework and was proposed in [4] for the purpose of tracking machine and human resource capability through the assignment of skills and skill levels. This paper extends on our previous works and proposes a Fuzzy Inference System based approach for developing the functions of resource capability assessment and personnel selection as a part of the resource capability evaluation module.

Recent works addressing the personnel selection problem use a fuzzy approach as fuzzy set theory is able to deal with the complexity of real-world decision problems where uncertain and imprecise knowledge and possibly vague preferences have to be considered. Golec and Kahya [5] presented a hierarchical structure for selecting and evaluating an employee through a competency-based fuzzy model. The lower level evaluates the employee according to measure indicators of the factors considered using a heuristic algorithm. The top level then selects the employee using a fuzzy rule-base approach based on the factors representing the organization's goals. Dursun and Karsak [6] introduced a fuzzy multi-criteria decision making (MCDM) method which is apt in managing information assessed using both linguistic and numerical scales in a decision making problem with multiple information sources. The personnel selection problem was used to illustrate the performance of the proposed method. Kelemenis and Askounis [7] used a fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach which incorporated a new measurement for the ranking of the alternatives based on the veto concept. Veto expresses the power of every decision maker to negate the selection of an alternative as a solution when this alternative performs worse than the veto set on the respective criterion. The ultimate decision criterion is not the similarity to the ideal solution but the distance from the imposed veto thresholds. Güngör *et al*. [8] proposed a fuzzy analytic hierarchy process (AHP) approach to solve the personnel selection problem. In the fuzzy AHP method, the pair-wise comparisons in the judgement matrix are fuzzy numbers and use fuzzy arithmetic and fuzzy aggregation operators. Petrovic-Lazarevic [9] also used AHP in her personnel selection fuzzy model. The two-level model consists of short list and hiring decisions and each of the levels in the three-level AHP used relates to the preliminary selection, hiring decision and expected utility of hiring the successful candidate, respectively.

One of the main motivations for solving the personnel selection problem is to minimize subjective judgment in the process of decision making. This motivation holds true for the work presented in this paper. The objective of this research is to develop a resource capability assessment methodology which allows managers to assess how well a worker's current skill set or capability matches up to that required by his job-role and to facilitate any training actions necessary based on the results of the assessment. By using the same methodology to assess all employees, managers can ensure consistent and comparable results. Similarly, the assessment procedure can also be used for the purpose of personnel selection to select the most appropriate employee for a job vacancy.

The organization of the paper is as follows: first, basic concepts of a Fuzzy Inference System (FIS) are introduced and the FIS structure for capability assessment is constructed. Second, the two stage resource assessment process is explained in detail. Then, a case study is provided to demonstrate the implementation of the proposed methodology, and experimental results are presented. The paper is completed by the conclusion.

2 Fuzzy Inference System

Fuzzy inference is a method of interpreting values in the input vector and assigning values to the output vector based on a set of rules. A Fuzzy Inference System (FIS) can be used to aid decision making and has been widely applied in different areas such as robotics, scheduling, supplier evaluation and investment selection [9, 10, 11]. A FIS is built based on the idea of fuzzy sets and fuzzy numbers.

2.1 *Fuzzy Sets*

A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership by generalizing the characteristic function to allow all values between zero and one. Let *X* be a collection of objects called the universal set. Every other collection of objects will be a subset of *X*. A fuzzy subset *F* of *X* is defined by its membership function, *F(x)*, whose values can be any number in the interval [0, 1]. The value of *F(x)* determines the grade of membership of *x* in fuzzy set *F*, and is often denoted by $\mu(x)$. If $\mu(x)$ is only zero or one, then the characteristic function is simply of a crisp, non-fuzzy, set *F*. In other words, crisp sets are special cases of fuzzy sets when membership values are always 0 or 1. In general, *x* belong to *F* if $\mu_F(x) = 1$, *x* does not belong to *F* if $\mu_F(x) = 0$, and *x* is in *F* with membership $\mu_F(x)$ if $0 < \mu_F(x) < 1$ [12].

2.2 *Fuzzy Numbers*

Fuzzy numbers represent a number of whose value is somewhat uncertain. They are a special kind of fuzzy set whose members are numbers from the real line and thus infinite in extent. Conventionally, fuzzy numbers are convex and have a finite area. Aside from this requirement, they can be of almost any shape, but are frequently triangular (piecewise linear), s-shape (piece-wise quadratic) or normal (bell-shaped). Trapezoidal, in which membership is 1 in an interval within, is also common [12]. A triangular fuzzy number *T* can be defined by a triplet (a, b, c) as seen in Figure 1. The corresponding membership function $\mu_T(x)$ can be defined as:

$$\mu_T(x) = \begin{cases} \frac{x-a}{b-a}, a \leq x \leq b, \\ \frac{x-c}{b-c}, b \leq x \leq c, \\ 0, \ otherwise \end{cases} \tag{1}$$

It was suggested that triangular fuzzy numbers are appropriate for quantifying the vague information about most decision problems including personnel selection due to their simplicity and their intuitive and computational-efficient representation [13].

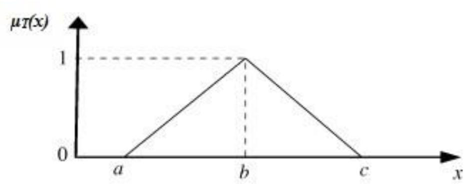

Figure 1: Membership Function of a Triangular Fuzzy Number

2.3 *Formulating the FIS for Resource Capability Assessment*

In literature, there are two basic approaches of fuzzy system modelling, i.e. linguistic fuzzy modelling and precise fuzzy modelling [14]. Linguistic fuzzy modelling, also known as the Mamdani approach, has high interpretability but lacks accuracy. On the other hand, precise fuzzy modelling, such as the Sugeno-type fuzzy inference, exhibits high accuracy but at the cost of interpretability. The accuracy of a fuzzy model indicates how closely it can represent the system, while interpretability is a measure of understanding of the system behaviour and expressing it through the model. Mamdani FIS, unlike Sugeno-type FIS, requires only a small input-output database for tuning and can interpret system behaviour between the discrete data. It is more intuitive and suited to human input. Therefore, we have chosen to use a Mamdani inference engine for our proposed fuzzy model for resource capability assessment.

In the present problem of determining how well a resource's capabilities match up to those required by the allocated job-role, input variables used are the average absolute difference in Technical, Soft and Personal skill levels between those of the resource and those required by the job-role while the output is the assessed score which can be used for ranking and decision making. During fuzzification, the antecedent variables of the system are converted into fuzzy variables using fuzzy sets. The performances of the popular Triangular, Trapezoidal and Gaussian membership functions (MFs) were compared. In the case of the current problem of assessing and ranking resource candidates, both Triangular and Trapezoidal functions produced similar results, while Gaussian functions proved to be better at differentiating resource capabilities and was able to discern all candidates with minimal tie rankings. Hence, Gaussian MFs were chosen to describe the fuzziness of input and output variables.

To initialize FIS design, a decision was made on the number, shape and location parameters of the membership functions. Bearing in mind that the absolute difference in skill levels is used to assess resource capabilities in relation to the assigned job-role, that is, a perfect match-rate would result in a zero-value input, the minimum fuzziness points of the MFs were placed in the universe of discourse (operating range) of the input variables as shown in Figure 3. The operating range of the input variables was determined by examining the maximum absolute difference values between possible skill levels. Note that although Gauss MFs were used to describe those input values as belonging to Excellent, Good or Average in terms of match-rate, an S-MF was used for the linguist term of Poor match-rate.

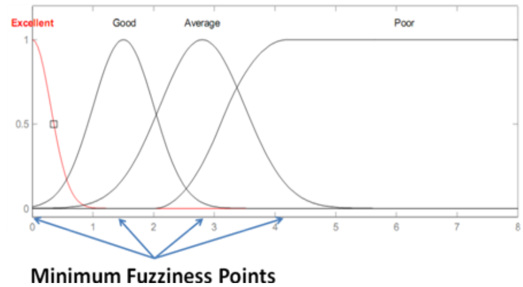

Figure 2: Fuzzy Membership Functions of the three Input Variables

Beyond the set threshold value, all input values that represent a significant difference in skill levels between that of the resource and that required by the job will be considered a Poor match.

The rule-base of the FIS relates the fuzzy antecedent and consequent variable using *if-then* statements and has the following structure:

If s_1 is M_{i1} and, ...s_3 is M_{i3} then O is A_i

Here i (i=1,...,n) is the rule number, M_{i1},...M_{i3} are the membership functions in the antecedent part, s_1,...,s_3 are the input variables signifying the average absolute difference in Technical, Soft and Personal skill levels. O is the single output variable and represents the evaluation score. A_i is the membership function in the fuzzy consequent O as shown in Figure 4. For example, *if* (Technical is Excellent) *and* (Soft is Excellent) *and* (Personal is Excellent) *then* (Score is Excellent). It can be seen that there is an inverse relationship between the inputs and the output, the smaller the average absolute difference between skill levels, the higher the match-rate and hence evaluation score. Defuzzification of the output uses the centroid method to produce the final crisp score value.

Ideally, the total number of rules is derived from the number of MFs and consequent variables using the following relationship:

$$N_r = \prod_{k=1}^{n} m_k \tag{1}$$

Where N_r is the total number of rules, n is the number of input variables and m_k is the number of linguistic terms of kth input variable. For example, there are three inputs and each input has four MFs, then the total number of rules in our case is 4^3, which is 64 rules.

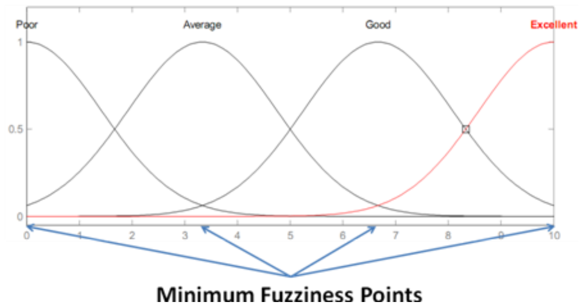

Figure 3: Fuzzy Membership Functions of the Output Variable

The rule-base was formulated such that there is a bias towards the importance of the Technical skills input. This was done in consideration of the assessment process in real companies where having the technical capabilities of the job requirement is the most important deciding factor. This is followed by Soft skills not directly related to the job-role, and Personal skills such as attitude, motivation, work-ethics and other personal values and characteristics.

3 Two Stage Assessment Process

There are two stages to the resource capability assessment procedure. The first of which is data preparation and processing, and the second is fuzzy inference using the designed FIS to obtain the final assessment score.

3.1 *Data Processing*

Prior to carrying out resource capability assessment for any job-role, it is necessary to define the required skills and skill levels for the job-role as well as set up the skill sets of considered resources (candidates). Each skill is defined as Technical (TS), Soft (SS) or Personal (PS) based on the role requirements and also weighted as Essential (E), Very Important (V), Important (I) or Preferred (P). The more important the skill, the greater the penalty for under-qualification when comparing the level of resource skill to that required by the role. Similarly, a small penalty is also placed on over-qualified skills, although in this case, those of less importance are given a relatively greater penalty. This means that resources with skill sets and levels that exactly or closely match those required by the job-role will score higher than those with significantly over-qualified or under-qualified skill sets.

An algorithm for determining the weighted average of the absolute difference in Technical, Soft and Personal skills of an assessed resource was created. The pseudo-code is given as follows:

```
i=0; j=0; k=0; a=0; b=0; c=0;
n=Total number of Data Entries for
Candidate;
for (n!=0)
        *Find Difference between Required
        and Actual Skill levels*
        Difference=Required-Entry;

        *Apply Weighting*
        *For Under-qualifying skills*
        if (D>=0)
                if (W==E then D=D*1.0);
                if (W==V then D=D*0.7);
                if (W==I then D=D*0.5);
                if (W==P then D=D*0.3);

        *For Over-qualifying skills*
        else if (D<0)
                if (W==E then D=D*0.01*-1);
                if (W==V then D=D*0.03*-1);
                if (W==I then D=D*0.05*-1);
                if (W==P then D=D*0.07*-1);

        *Check Skill Type*
        if (Type==TS then i++, a+=D);
        else if (Type==SS then j++, b+=D);
        else if (Type==PS then k++, c+=D);
        else (Error -> No Type Specified);
        n-1;

TD=a/i;
SD=b/j;
PD=c/k;
```

The weightings used for over/under-qualified E, V, I and P skills were determined by trial and error. A significantly smaller penalty is given to over-qualified skills. The final values for TD, SD, and PD are the weighted average of the absolute difference in skill levels of Technical, Soft and Personal skills, respectively. These are also the values that are used as the input variables to the designed FIS used in the second stage of the assessment process.

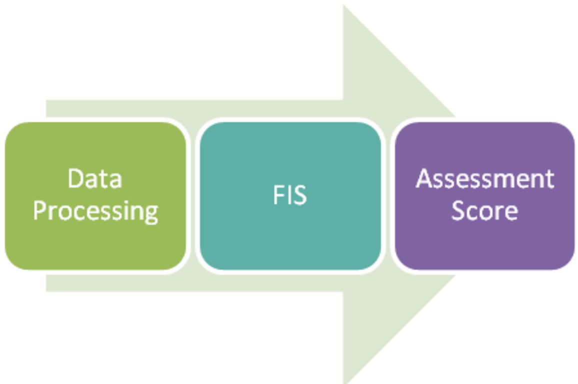

Figure 4: Block Diagram illustrating the Resource Capability Assessment Process

3.2 *FIS Application*

The FIS formulated for resource capability assessment (outlined in section 2.3) takes in three inputs in the form of weighted averages of the absolute difference in Technical, Soft and Personal skill levels and uses Mamdani-type fuzzy inference to produce an output assessment score. This score can then be used to rank the assessed resources and facilitate necessary training actions or aid in any other decision-making processes.

4 Case Study

The proposed resource capability assessment approach was implemented as a part of the CERES system [3, 4] and its performance validated using data provided by an industry partner.

4.1 *Implementation Environment*

The CERES system is hosted online to allow easy access for industry partners for evaluation and feedback. A Web hosting service was used to achieve this. The system's website was designed using Visual Web Developer 2008 Express utilizing ASP.NET development with C#. All database management is done using Microsoft SQL server 2008. The proposed two-stage resource capability assessment approach was implemented as a part of the capability evaluation module of the CERES system. The first stage data processing was completed using SQL data manipulation methods and stored procedures. The second-stage FIS was implemented as a Stand-Alone C-Code Fuzzy Inference Engine utilising MATLAB resources. The designed FIS is read by the inference engine as a .fis file alongside SQL generated input data to perform the fuzzy inference directly.

4.2 *System Testing*

In collaboration with an industry partner, the required Technical skills, relevant Soft and Personal skills, and their associated skill levels were defined for a 'Manager' job-role. Each of the required skills was also weighted as E, V, I or P. Three test sets of five potential candidates were generated; these were of high match-rate, medium match-rate, and low match-rate, respectively. The aim is to validate the ability of the FIS to generate accurate assessment scores for each candidate and rank them accordingly.

For this particular industry partner, evaluation rating of a skills range from Poor, Average, Good, Very Good and Excellent. These correspond to skill levels of 1, 3, 5, 7 and 9 respectively. Following data processing, Table 1 below shows the three inputs into the second-stage FIS for each candidate of the three test groups. Note again that the inputs are the weighted averages of the absolute difference in skill levels between that of the resource and that required by the job-role. A value of zero difference is most favourable.

Table 1: FIS input values of candidates in the High, Medium and Low match-rate test sets.

	TD	SD	PD
HC1	0.00	0.00	0.00
HC2	0.00	0.00	0.16
HC3	0.00	0.15	0.00
HC4	0.12	0.00	0.00
HC5	0.12	0.15	0.16
MC1	0.25	0.57	0.16
MC2	0.60	1.40	0.58
MC3	1.47	1.13	1.52
MC4	3.31	1.07	4.18
MC5	3.77	1.53	5.02
LC1	3.97	2.55	5.02
LC2	3.97	2.70	5.18
LC3	4.09	2.55	5.18
LC4	4.09	2.70	5.02
LC5	4.09	2.70	5.18

4.3 *Experimental Results*

Table 2 shows the crisp output scores generated by the FIS for each candidate in the test sets. A colour scale system is used to aid ranking and differentiate candidates with varying performances. The use of colours will also help highlight those resources in need of attention and training in the case of evaluation rather than selection assessments.

Table 2: FIS output score for candidates in the High, Medium and Low match-rate test sets.

	O
HC1	8.80
HC2	8.76
HC3	8.76
HC4	8.69
HC5	8.67
MC1	7.52
MC2	6.57
MC3	5.96
MC4	3.38
MC5	3.31
LC1	2.24
LC2	2.23
LC3	2.07
LC4	2.05
LC5	2.05

The results obtained indicate that the proposed assessment approach is able to pick up minor differences in the significant Technical skills input. Minor differences in the less important Soft and Personal skills inputs are not as vital for ranking and ties are possible. Overall, the generated assessment scores accurately reflect how well the capability of a resource matches up to those required by the assigned job-role.

4.4 *Industry Application and User Interface*

Following the successful experimentation with the test sets, the FIS-based approach to resource capability assessment was applied to a number of real world assessment scenarios in our industry partner company. The proposed two-stage method was able to generate accurate assessment scores and correctly rank candidates for hiring/promotion decisions as well as identify training needs in those resources already in assigned job-roles. Assessment results were checked against rankings carried out manually by management and were found to be satisfactory. The system was able to save time and minimize subject judgement in resource management decisions in industry and was found to be a valuable tool.

An aesthetic user interface was created for companies to carry out assessment. Managers are able to define job-roles and their required skill and skill levels, define resources and their skill sets, assess candidates for a particular job-role or assess resources currently assigned to a job-role. Figure 5 shows a screen shot of the user interface displaying the results after an assessment. Worker names have been made confidential. Indication is given on the level of match-rate for Technical, Soft and Personal skills, as well as the final assessment score. The colour scale is used to highlight varying levels of resource performance and the date of the latest evaluation is also provided.

5 Conclusions

This paper presented a two-stage fuzzy inference system approach to resource capability assessment which was implemented as a function of the resource capability evaluation module of the CERES system introduced in our previous works. In the first stage, SQL data processing methods were used to determine the weighted average of the absolute difference in Technical, Soft and Personal skills between the assessed resource and that required by the considered job-role. These values were then used as the inputs into the second stage FIS to generate a final output assessment score. The implemented function was tested using data from an industry partner and was also applied in several real-world resource assessment scenarios. Results show that the proposed method can be successfully used for personnel selection in employment and promotion decisions, as well as for general resource evaluation to help facilitate training and other management decisions.

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Candidate Evaluation total: 8 Evaluate New Candidate Evaluation

Current Role	Candidate	Technical Skill Match	Soft Skill Match	Personal Skill Match	Score	Evaluation Date
Plastics Process Worker (Day)	Worker 1	Excellent	Excellent	Excellent	8.77	15/12/2011
Plastics Process Worker (Day)	Worker 2	Excellent	Excellent	Excellent	8.28	15/12/2011
Plastics Process Worker (Day)	Worker 3	Good	Good	Excellent	8.00	15/12/2011
Plastics Process Worker (Day)	Worker 4	Excellent	Good	Excellent	7.93	15/12/2011
Plastics Process Worker (Day)	Worker 5	Good	Good	Excellent	6.54	15/12/2011
Plastics Process Worker (Day)	Worker 6	Good	Good	Excellent	6.46	15/12/2011
Plastics Process Worker (Day)	Worker 7	Good	Good	Excellent	6.42	15/12/2011
Applicant	Applicant 1	Poor	Poor	Excellent	3.37	15/12/2011

Figure 5: System User Interface – Resource Ranking after Assessment

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