Belief-Rule-based Decision Support System for Evaluating of Job Offers

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ABSTRACT
The word 'Job' term as a regular activity performed in exchange for payment is considered as one of the most important activities for many families worldwide .Evaluation is necessary when more than one opportunity come to an individual personality. Then it requires the job offer evaluation. To fulfill their desired goal, it is the' evaluation' which assesses them well. This involves many factors to be measured and evaluated. These factors are expressed both in objective and subjective ways where as a hierarchical relationship exists among the factors. In addition, it is difficult to measure qualitative factors in a quantitative way, resulting incompleteness in data and hence, uncertainty. Besides it is essential to address the subject of uncertainty by using apt methodology; otherwise, the decision to choose a job will become inapt. Therefore, this paper demonstrates the application of a novel method named belief rule-based inference methodology-RIMER base decision support system(DSS), which is capable of addressing suitable job by taking account of large number of criteria, where there exist factors of both subjective and objective nature.

Keywords
Multiple criteria decision analysis (MCDA), uncertainty, belief rule base (BRB), evidential reasoning (ER), and decision support system (DSS).

1. INTRODUCTION
When we attempt to evaluate of job offers, it involves multiple criterions such as, location, salary, job content, long-term prospects, safety, and environment, proximity to hospitals, main road, office, transportation cost and utility cost, which are quantitative and qualitative in nature[20][21]. Numerical data which uses numbers is considered as quantitative data and can be measured with 100% certainty.[4] . On the contrary, qualitative data is descriptive in nature, which defines some concepts or imprecise characteristics or quality of things [5].Hence, this data can't describe a thing with certainty since it lacks the precision and inherits ambiguity, ignorance, vagueness. Consequently, it can be argued that qualitative data involves uncertainty since it is difficult to measure concepts or characteristics or quality of a thing with 100% certainty."Quality of Location" is an example of equivocal term since it is an example of linguistic term. Hence, it is difficult to extract its correct semantics (meaning). However, this can be evaluated using some referential value such as excellent, good, average and bad. Therefore, it can be seen that qualitative criterions which have been considered in selecting a job involves lot of uncertainties and they should be treated with appropriate methodology is RIMER, which is connect to Evidential reasoning(ER) is a multi-criteria decision analysis (MCDA) method[13][14]. ER deals with problems, consisting of both quantitative and qualitative criteria under various uncertainties such as incomplete information, vagueness, ambiguity [7].The ER approach, developed based on decision theory in particular utility theory [1][11], artificial intelligence in particular the theory of evidence [9][10]. It uses a belief structure to model a judgment with uncertainty. Qualitative attribute such as location or safety needs to be evaluated using some linguistic referential value such as excellent, average, good and bad etc[20][21]. This requires human judgment for evaluating the attributes based on the mentioned referential value. In this way, the issue of uncertainty can be addressed and more accurate and robust decision can be made. The belief rule-based inference methodology-RIMER [15] has addressed such issue by proposing a belief structure which assigns degree of belief in the various referential values of the attributes.

In section 2 will briefly represent belief rule base inference methodology-RIMER. Section 3 will demonstrate the application of BRB in job evaluation problem. Section 4 will represent the results and achievement. Finally section 5 will conclude the research.

2. RIMER TO DEVELOP DSS
In RIMER, Belief Rule Base (BRB) can capture complicated nonlinear causal relationships between antecedent attributes and consequents, which is not possible in traditional IF-THEN rules. BRB is used to model domain specific knowledge under uncertainty, and the ER approach is employed to facilitate inference. This section introduces BRB as a knowledge representation schema under uncertainty as well as inference procedures of RIMER.

2.1 Modeling Domain Knowledge using BRB

Belief Rules are the key constituents of a BRB, which include belief degree. This is the extended form of traditional IF-THEN rules. In a belief rule, each antecedent attribute takes referential values and each possible consequent is associated with belief degrees[15]. The knowledge representation parameters are rule weights, attribute weights and belief degrees in consequent attribute, which are not available in traditional IF-THEN rules. A belief rule can be defined in the following way.

$$R_k : \begin{cases} \text{IF } (P_1 \text{ is } A_1^k) \cap (P_2 \text{ is } A_2^k) \cap \dots\dots \cap P_{T_k} \text{ is } A_{T_k}^k \\ \text{THEN } \{(C_1, \beta_{1k}), (C_2, \beta_{2k}), \dots\dots, (C_N, \beta_{Nk})\} \end{cases} \quad (1)$$

$$R_k : \left(\beta_{jk} \geq 0, \sum_{j=1}^{N} \beta_{jk} \leq 1\right) \text{ with a rule weight } \theta_k, \text{attribute}$$

$$\text{weights } \delta_{k1}, \delta_{k2}, \delta_{k3}, \dots\dots, \delta_{kT_k} \quad k \in \{1, \dots\dots, L\}$$

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Where P_1, P_2, P_3 ... $P_{T_k} P_{Tk} P_{Tk}$ represent the antecedent attributes in the kth rule. $A_i^k (i = 1, \dots\dots, T_k, k = 1, \dots\dots, L)$ $A_i^k (i = 1, \dots\dots, T_k, k = 1, \dots\dots, L)$ represents one of the referential values of the ith antecedent attribute P_i in the kth rule . C_j C_j C_j is one of the consequent reference values of the belief rule. $\beta_{jk}(j = 1, \dots\dots, N, \; k = 1, \dots\dots, L)$ $\beta_{jk}(j = 1, \dots\dots, N, \; k = 1, \dots\dots, L)$ $\beta_{jk}(j = 1, \dots\dots, N, \; k = 1, \dots\dots, L)$ is one of the the belief degrees to which the consequent reference value C_j C_j C_j is believed to be true. If $\sum_{j=1}^{N} \beta_{jk} = 1$ $\sum_{j=1}^{N} \beta_{jk} = 1$ the kth rule is said to be complete; otherwise, it is incomplete. T_k is the total number of antecedent attributes used in kth rule L is the number of all belief rules in the rule base. N is the number of all possible consequent in the rule base.For example a belief rule to assess cost of communicate for job can be written in the following way.

$$R_k : \begin{cases} IF \quad Transportation\ cost \quad is \quad good \quad AND \quad utility\ cost \quad is \quad good \\ THEN \quad cost \quad is \\ \{(Excellent, (0.00)), (good, (1.00)), (average, (0.00))\} \end{cases} \quad (2)$$

Where {(Excellent, 0.00), (Good, 1.00), (Average, 0.00)} is a belief distribution for pain consequent, stating that the degree of belief associated with Excellent is 0%, 100% with Good and 0% with Average. In this belief rule, the total degree of belief is (0+1+0) =1, hence that the assessment is complete.

2.2 BRB Inference using ER

The ER approach [7] [18]developed to handle multiple attribute decision analysis (MADA) problem having both qualitative and quantitative attributes. Different from traditional MADA approaches, ER presents MADA problem by using a decision matrix, or a belief expression matrix, in which each attribute of an alternative described by a distribution assessment using a belief structure. The inference procedures in BRB inference system consists of various components such as input transformation, rule activation weight calculation, rule update mechanism, followed by the aggregation of the rules of a BRB by using ER [15][16][18].

The input transformation of a value of an antecedent attribute Pi consists of distributing the value into belief degrees of different referential values of that antecedent. This is equivalent to transforming an input into a distribution on referential values of an antecedent attribute by using their corresponding belief degrees [14]. The ith value of an antecedent attribute at instant point in time can equivalently be transformed into a distribution over the referential values, defined for the attribute by using their belief degrees .The input value of P_i P_i, which is the **i**th antecedent attribute of a rule, along with its belief degree ε_i ε_i is shown below by equation (3). The belief degree ε_i $\varepsilon_i$to the input value is assigned by the expert in this research.

$$H(P_i, \varepsilon_i) = \{(A_{ij}, \alpha_{ij}), j = 1, \cdots, j_i\}, \; i = 1, \dots\dots, T_k \quad (3)$$

Here H is used to show the assessment of the belief degree assigned to the input value of the antecedent attribute. In the above equation A_{ij} A_{ij} (ith value) is the jth referential value of the input P_i. P_i. α_{ij} α_{ij} is the belief degree to the referential value A_{ij} A_{ij} with $\alpha_{ij} \geq 0$ $\alpha_{ij} \geq 0$. $\sum_{j=1}^{j_i} \alpha_{ij} \leq 1 (i = 1, \dots, T_k)$ $\sum_{j=1}^{j_i} \alpha_{ij} \leq 1 (i = 1, \dots, T_k)$, and j_i j_i is the number of the referential values.

For example, the input 0.92 for cost is equivalently transformed to{(Excellent,0.87),(Good,0.11),(Average,0.02)}. The input value of an antecedent attribute is collected from the expert in terms of linguistic values such as ‘Excellent’, ‘Good’ , ‘Average’ and ‘Bad’.This linguistic value is then assigned degree of belief ε_i ε_i by taking account of expert judgment. This assigned degree of belief is then distributed in terms of belief degree α_{ij} α_{ij} of the different referential values A_{ij} A_{ij} [Excellent,Good ,Average, Bad] of the antecedent attribute. The above procedure of input transformation is elaborated by equations (4 and 5) given below. However, when a hospital is located 1.3 km of the place, it can be both excellent and average. However, it is important for us to know, with what degree of belief it is excellent and with what degree of belief it is average. This phenomenon can be calculated with the following formula.

$$\beta n, i = \frac{h_{n+1} - h}{h_{n+1}, i - h_{n,i}}, \beta_{n+1,i} = 1 - \beta_{n,i} \dots\dots\dots\dots (4)$$

$$if \quad hn, i \leq h \leq h_{n+1,i} \dots\dots\dots (5)$$

Here, the degree of belief $\beta_{n,i}$ is associated with the evaluation grade ‘average’ while $\beta_{n+1,i}$ is associated with the upper level evaluation grade i.e. excellent. The value of h_{n+1} is the value related to excellent, which is considered as 1km i.e. the location of the hospital. The value of h_{n+1} is related to average, which is 1.5 km. Hence, applying equation (2) the distribution of the degree of belief with respect to 1.3 Km of the location of the hospital from the job place can be assessed by using equation (2) and the result is given below:

{(Excellent, 0.4), (Good, 0.6), (Average, 0), (Bad,0)}, When the ***k***th rule is activated, the weight of activation of the ***k***th rule, w_k is calculated by using the flowing formula [17][18].

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{j=1}^{L} \theta_j \alpha_j} = \frac{\theta_k \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\overline{\delta_{ki}}}}{\sum_{j=1}^{L} \theta_j \left[\prod_{l=1}^{T_k} \left(\alpha_l^j\right)^{\overline{\delta_{jl}}}\right]}$$

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and

$$\overline{\delta_{ki}} = \frac{\delta_{ki}}{max_{i=1,\dots,T_k}\{\delta_{ki}\}} \quad \overline{\delta_{ki}} = \frac{\delta_{ki}}{max_{i=1,\dots,T_k}\{\delta_{ki}\}} \qquad (6)$$

Where $\overline{\delta_{ki}}$ is the relative weight of P_i used in the ***k***th rule, which is calculated by dividing weight of P_i with maximum weight of all the antecedent attributes of the kth rule. By doing so, the value of $\overline{\delta_{ki}}$ becomes normalize, meaning that the range of its value should be between 0 and 1. $\alpha_k = \prod_{i=1}^{T_k} \left(\alpha_i^k\right)^{\overline{\delta_{ki}}}$ is the combined matching degree, which is calculated by using multiplicative aggregation function.

When the ***k***th rule as given in.(1) is activated, the incompleteness of the consequent of a rule can also result from its antecedents due to lack of data. An incomplete input for an attribute will lead to an incomplete output in each of the rules in which the attribute is used. The original belief degree $\overline{\beta_{ik}}$ in the ***i***th consequent C_i of the ***k***th rule is updated based on the actual input information as [15][17][18].

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k}\left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj}\right)}{\sum_{t=1}^{T_k} \tau(t,k)} \quad \beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k}\left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj}\right)}{\sum_{t=1}^{T_k} \tau(t,k)}$$

(7)

Where,

$$(t,k) = \begin{cases} 1, & if\ P_i\ is\ used\ in\ defining\ R_k (t = 1, \dots, T_k) \\ 0, & otherwise \end{cases}$$

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Here $\overline{\beta_{ik}}$ is the original belief degree and β_{ik} is the updated belief degree.

Due to the incomplete input for 'Cost' ,the belief degree of the connected rules needs to be modified to show the incompleteness by using (7)

$$\beta_{ik} \equiv \overline{\beta}_{ik} \frac{1.6}{2} = \overline{\beta}_{ik} * 0.8, \qquad i = 1,2,3; k = 1,\dots 9.$$

Therefore $0 < \sum_{i=1}^{3} \beta_{ik} < 1$ for all rules that are associated with 'Cost'. Using the sub rule base, the assessment result for 'Cost' is obtained using DSS system as Pain:{(Excellent, 0.66), (Good,0.23),(Average,0.02), (Bad,0.00),(Unknown,0.09)} where" Unknown " in the above result means that the output is also incomplete input. ER approach is used to aggregate all the packet antecedents of the ***L*** rules to obtain the degree of belief of each referential values of the consequent attribute by taking account of given input values P_i of antecedent attributes. This aggregation can be carried out either using recursive or analytical approach. In this research analytical approach[19] has been considered since it is computationally efficient than recursive approach [14][20][21], because analytical approach deal with all parameter such as rule weight, attribute weight ,belief degree, utility etc. For this why there is no chance of absence of any parameter. The conclusion *O(Y),* consisting of referential values of the consequent attribute, is generated. Equation (8) as given below illustrates the above phenomenon. :

$$O(Y) = S(P_i) = \{(C_j, \beta_j), \ j = 1, \dots, N\}$$

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(8)

Where β_j denotes the belief degree associated with one of the consequent reference values such as C_j. The β_j is calculating by analytical format of the ER algorithm [3] as illustrated in equation (9).

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L}\left(\left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right) - \prod_{k=1}^{L}\left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]}{1 - \mu \times \left[\prod_{k=1}^{L} 1 - \omega_k\right]} \qquad (9)$$

With

$$\mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} \left(\omega_k \beta_{jk} + 1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right) - (N-1) \times \prod_{k=1}^{n} \left(1 - \omega_k \sum_{j=1}^{N} \beta_{jk}\right)\right]^{-1}$$

The final combined result or output generated by ER is represented by

$$\{(C_1, \beta_1), (C_2, \beta_1), (C_3, \beta_1), \dots \dots \dots, (C_N, \beta_N)\}$$

$$\{(C_1, \beta_1), (C_2, \beta_1), (C_3, \beta_1), \dots \dots \dots, (C_N, \beta_N)\}$$

Where β_j is the final belief degree attached to the ***j***th referential value C_j of the consequent attribute, obtained after combining all activated rules in the BRB by using ER.

2.3 Output of the BRB System

The output of the BRB system is not crisp/numerical value. Hence, this output can be converted into crisp/numerical value by assigning utility score to each referential value of the consequent attribute [17] -

$$H(A^*) = \sum_{j=1}^{N} u(C_j) B_j \quad H(A^*) = \sum_{j=1}^{N} u(C_j) B_j$$

(10)

Where $H(A^*)$ is the expected score expressed as numerical value and $u(C_j)$ is the utility score of each referential value. For example, in this paper the overall assessment result is {(Excellent,0.55),(Good, 0.25),(Average,0.20),(Bad,0.00)}for Job evaluation(S) of a specific job, then the expected utility score is 0.675 or 68% which represents good risk for job. In this paper the RIMER methodology to address various type of uncertainty such as incompleteness, ignorance and impreciseness by using equation (7) and equation (11).The incompleteness as mentioned occurs due to ignorance, meaning that belief degree has not been assigned to any specific evaluation grade and this can be represented using the equation as given below.

$$\beta_H = 1 - \sum_{n=1}^{N} \beta_n \text{........(11)}$$

Where β_H is the belief degree unassigned to any specific grade . If the value of β_H is zero then it can argued that there is an absence of ignorance or incompleteness. If the value of β_H is greater than zero then it can be inferred that there exists ignorance or incompleteness in the assessment.

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k} \left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj} \right)}{\sum_{t=1}^{T_k} \tau(t,k)}$$

3. BRB DSS ARCHITECTURE

Architectural design represents the structure of data and program components that are required to build a computer-based system. It also considers the pattern of the system organization, known as architectural style. BRB DSS adopts the three-layer architecture, which consist of presentation layer, application layer and data processing layer as shown in figure 1.

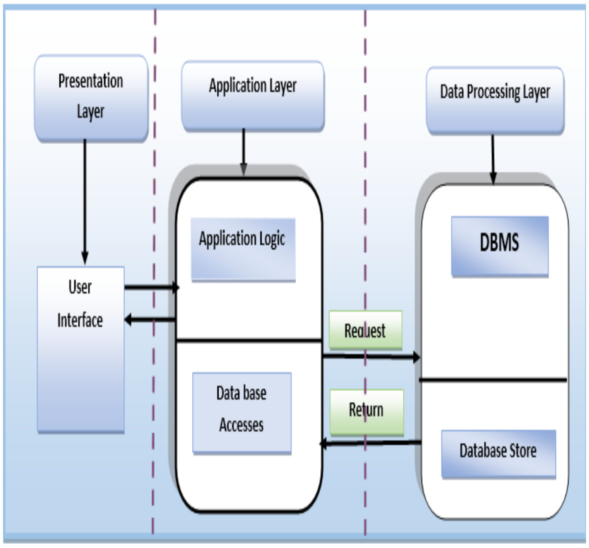

Fig 1: BRB DSS Architecture

3.1 System Components

The input clarification of input antecedent W11(Proximity to main road), W12 (Proximity to Office),W13(Proximity to Hospitals),W21(Transportation Cost),W22(Utility Cost),W31(Location),W32(Salary), W33(Safety), W34(Job Content),W35(Environment),W36(Long-term Prospects) are transformed to referential value by equation (4),(5) on behalf of expert. The input clarifications of this BRB system transformed to referential is shown in table 1.

Table 1. The Input are Transformed in Referential Value

Sl.No.	Input Antecedent	Expert Belief	Referential Value			
			Excellent	Good	Average	Bad
0	W11	1.0	1	0	0	0
1	W12	0.5	0.1	0.7	0.2	0
2	W13	0.8	0.5	0.5	0	0
3	W21	0.5	0.1	0.8	0.1	0
4	W22	1	0.8	0.2	0	0
5	W31	0.5	0.1	0.4	0.5	0
6	W32	1	0.8	0.2	0	0
7	W33	1	0.8	0.2	0	0
8	W34	0.4	0.1	0.5	0.4	0
9	W35	0.5	0.5	0.4	0.1	0
10	W36	1	0.8	0.2	0	0

3.2 Knowledge Base Constructed using BRB

In present paper, we worked on job evaluation. In order to construct BRB knowledge base of this system we designed a BRB framework to job assessment according to domain expert. The BRB framework of job evaluation as illustrated in Figure 2, From the framework, it can be observed that input factors that determine suitable job. The BRB knowledge base has different traditional rule to assessment, which need to convertbeliefrules.

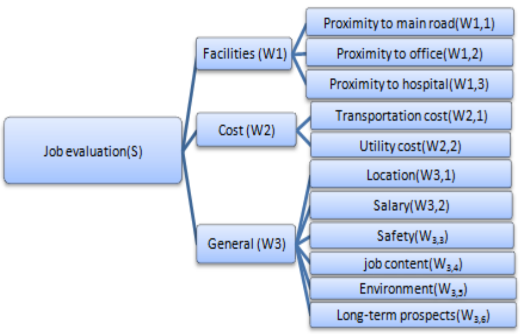

Fig 2: Hierarchical Relationship among job evaluation Variable

In such situations, belief rules may provide an alternative solution to accommodate different types and degrees of uncertainty in representing domain knowledge. A BRB can be established in the following four ways[15]- (1) Extracting belief rules from expert knowledge (2) Extracting belief rules by examining historical data; (3) Using the previous rule bases if available, and (4) Random rules without any pre-knowledge. In this paper, we constructed initial BRB by the domain expert knowledge. This BRB consists of four sub-rule-bases namely Facilities (W1), Cost(W2),General(W3), and Job evaluation(S). Facilities sub-rule-base has three antecedent attributes. Each antecedent attribute consists of four referential values. Hence, this sub-rule-base consists of 16 rules. The entire BRB (which consists of four sub-rule bases) consists of (64+16+4096+64) =4240 belief rules. It is assumed that all belief rules have equal rule weight; all antecedent equal weight, and the initial belief degree assigned to each possible consequent by two expert from accumulated the data. To better handle uncertainties, each belief rule considered the three referential values are Excellent (E), Good(G) , Average(A) and Bad(B)

Table 2: Initial Belief Rules of Sub-Rule-Base (Cost)

Rule No.	Rule Weight	IF		THEN			
		W21	W22	Cost(W2)			
				Excellent	Good	Average	Bad
0	1	E	E	0.8	0.2	0	0
1	1	E	G	0.4667	0.533	0	0
2	1	E	A	0.0667	0.933	0	0
3	1	E	B	0	0.933	0.1	0
4	1	G	E	0	0.8	0.2	0
5	1	G	G	0	0.666	0.3	0
6	1	G	A	0.3333	0.666	0	0
7	1	G	B	0	0.933	0.1	0
8	1	A	E	0	0.8	0.2	0
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
14	1	B	A	0.2	0	0.8	0
15	1	B	B	0	0.066	0.9333	0

An example of a belief rule taken from Table 2 is illustrated below.

R1: ***IF*** W21 is ‘E‘ ***AND*** W22 is ‘E‘

THEN Cost(W2) is {E (0.8), G (0.2), A (0.00),B(0.00)}

3.3 Inference Engine using ER

This BRB DSS designed using the ER approach [15][18][20][21]which is described in section 2.2. It is similar to traditional forward chaining. The inference with a BRB using the ER approach also involves assigning values to attributes, evaluating conditions and checking to see if all of the conditions in a rule are satisfied. The BRB inference process using the ER approach described by the following steps are input transformation, calculation of the activation weight, calculating combined belief degrees to all consequents, belief degree update and aggregate multiple activated belief rules.The inputs of data are of two types, objective and subjective. Input transformation of this system and input clarification are deduced in previous section and table I by using (4)(5). After the value assignment for antecedent , calculating the combined matching degrees between the inputs and the rule’s antecedents, the next step is to calculate activation weight for each packet antecedent in the rule base using (6). The belief degrees in the possible consequent of the activated rules in the rule base are updated using (7). Then aggregating all activated rules using the ER approach to generate a combined belief degree in possible consequents using (8)(9). Then expected result of job evaluation was calculated from its different consequents of factors. Finally, presenting the system inference results of job evaluation consequent which is not crisp/numerical value, then it is converted into crisp/numerical value for recommendation using equation (10).

3.4 BRB DSS Interface

System interface is an intermediate position that represents the interaction between user and system. Figure 3 represents the BRB system interface of this paper.

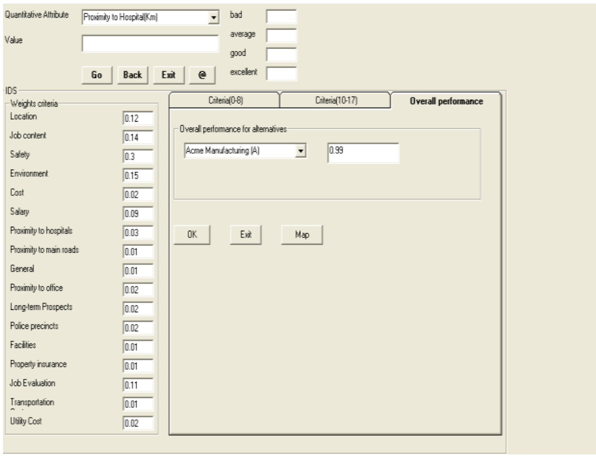

Fig 3: Interface of the DSS

4. RESULTS AND DISCUSSION

In the previous section, we have discussed about the RIMER method and how to implement it. Therefore, in this section we will look at the results from using this method on the different types of job. FIG 3 shows the assessment distribution which must be done first by employing the transformation equation. Any measurements of quality can be translated to the same set of grades as the top attribute which make it easy for further analysis. The assessments given by the Decision Maker (DM) in Figure 2 are fed into DSS and the aggregated results are yielded at the main criteria level (Figure 2)

The four alternatives (job sector) simulated data set with assessment outcome is presented in figure 6.. This figure represents overall assessment outcome from job sector information. The result of this system is measured in percentage for recommendation. The output of this system was generated based on output utility equation (10). In this paper, the utility score of (100-90)% assigned to ‘Excellent’,

Attributes	Acme Manufacturing (A)	Bankers Bank (B)	Creative Consulting (C)	Dynamic Decision Making (D)
Location	B(0.2)A(0.8)	G(0.4)E(0.6)	G(0.4)E(0.6)	E(1.0)
Job Content	G(0.4)E(0.6)	B(0.2)A(0.8)	B(0.2)A(0.8)	G(0.4)E(0.6)
Safety	B(0.2)E(0.8)	A(1.0)	G(1.0)	A(1.0)
Environment	E(1.0)	G(1.0)	G(0.4)E(0.6)	G(1.0)
Long-term Prospects	G(1.0)	B(0.2)E(0.8)	E(1.0)	B(0.2)A(0.8)
Proximity to Hospitals(Km)	2.3	2.6	2.4	2.0
Proximity to Office(Km)	2.0	1.6	1.0	2.0
Proximity to Main Road(Km)	1.4	1.0	2.1	2.5
Salary(Thousand)	1.0	1.6	1.6	2.0
Transportation Cost(Thousand)	2.3	1.0	1.1	1.4
Utility Cost(Thousand)	2.0	2.3	2.0	2.0

Fig 4:Assessment Scores Of Job Sector Based On Sub Criteria(E-Excellent, G-Good, A-Average, B-Bad)

Alternative	Excellent	Good	Average	Bad	Total Degree of belief
Acme Manufacturing (A)	0.40	0.50	0.00	0.10	1.00
Bankers Bank (B)	0.12	0.48	0.10	0.30	1.00
Creative Consulting (C)	0.18	0.52	0.10	0.20	1.00
Dynamic Decision Making (D)	0.18	0.40	0.40	0.02	1.00

Fig 5:The Overall Assessment (Alternatives)

Alternatives	Expected Utility Score/ BRB System Result	Manuel Result	Benchmark Result	Stage
Acme Manufacturing (A)	90%	75%	92%	Excellent
Bankers Bank (B)	85%	65%	87%	Good
Creative Consulting (C)	75%	80%	78%	Bad
Dynamic Decision Making (D)	80%	79%	82%	Average

Fig 6:Overall assessment

(85-89)% assigned to ‘Good’, (80-84)% assigned to ‘Average’ and (0-79)% assigned to ‘Bad’. In the case study, the job assessment of four job sector using this system, manual system and benchmark result is shown in figure 6. The historical results were considered as benchmark. From figure 4 it can be observed that DSS generated result has less deviation than from benchmark result. Hence, it can be argued that DSS output is more reliable than manual system. Therefore, it can be concluded that if the assessment of job offers evaluation is carried out by using the DSS, eventually this will play an important role in taking decision to avoid uncertainty issue. The possible expected utilities of each alternative generated by the DSS (Figure 6)(based on the given utility values for each grade above) .The job ranked based on the expected utility. The ranking of job is as follows: **Acme Manufacturing (A) > Bankers Bank (B)> Dynamic Decision Making (D)>Creative Consulting (C)**

5. CONCLUSION

The development and application of a belief rule based DSS to choose suitable job by using attribute of job sector have been presented. The prototype DSS is embedded with a novel methodology known as RIMER, allows the handling of various types of uncertainty and hence, be considered as a robust tool can be utilized in selecting suitable job. Consequently, the prototype DSS can handle various types of uncertainties found in job offer evaluations domain knowledge as well as in attribute/criterion of a job sector. This system can also provide a percentage of recommendation, which is more reliable and informative than from the traditional expert's opinion. The prototype DSS can only is used to select good job by using attribute of a job sector.

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