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Knowledge-based Decision Support System to Select Hospital Location

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Abstract: *The general public's demand of Bangladesh for safe health is rising promptly with the improvement of the living standard. However, the allocation of limited and unbalanced medical resources is deteriorating the assurance of safe health of the people. Therefore, the new hospital construction with rational allocation of resources is imminent and significant. The site selection for establishing a hospital is one of the crucial policy-related decisions taken by planners and policy makers. The process of hospital site selection is inherently complicated because of 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 suitable site will become inapt. Therefore, this paper demonstrates the application of a novel method named Evidential reasoning methodology -based intelligent decision system, which is capable of addressing suitable site for hospital 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, evidential reasoning (ER) and Knowledge-based Decision Support System (KDSS)*

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I. Introduction

When we try to select suitable site for hospital, it involves multiple criterions such as, location, safety, environment, parking space, Land cost, Risk, transportation cost and utility cost etc. 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 hospital location involves lot of uncertainties and they should be treated with appropriate methodology is 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 term such as excellent, average, good and bad etc[20][21]. This requires human judgment for evaluating the attributes based on the mentioned evaluation grades. In this way, the issue of uncertainty can be addressed and more accurate and robust decision can be made. The evidential reasoning (ER) [15] has addressed such issue by proposing a belief structure which assigns degree of belief in the various evaluation grades of the attributes.

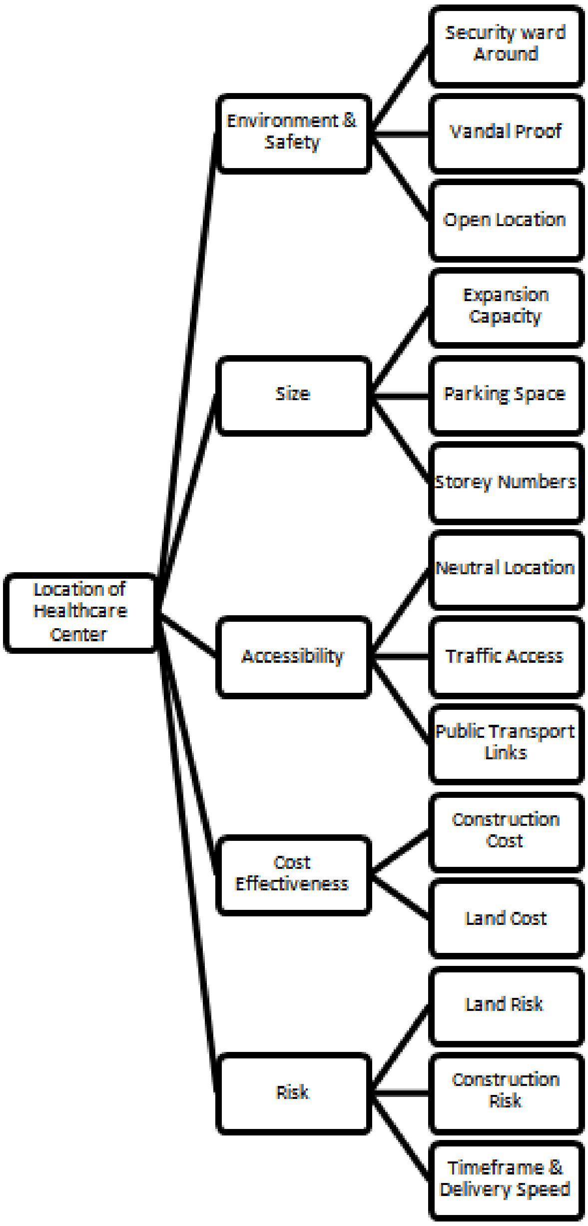

Figure 1: Hierarchical Relationship among location evaluation Variable

In section 2 will briefly represent hospital site selection problem oriented inference methodologyER algorithm. Section 3 will demonstrate the application of ER in hospital site selection problem. Section 4 will represent the results and achievement. Finally section 5 will conclude the research.

II. Evidential Reasoning Approach

The evidential reasoning algorithm is considered as the kernel of the ER approach. This algorithm has been developed based on an evaluation analysis model [22][23] and the evidence combination rule of the Dempster-Shafer (D-S) theory [15][18][19], which is well-suited for handling incomplete uncertainty [22]. The ER approach uses a belief structure to model an assessment as a distribution. It differs with other Multi Criteria Decision Making (MCDM) modeling methods in that it employs evidence-based reasoning process to derive a conclusion [13][14][20]. The main strength of this approach is that it can handle uncertainties associated with quantitative and qualitative data, related to MCDM problems [13][14] [20].

The ER approach consists of seven phases including 1) Information acquisition and representation or assessment, 2) weight normalization, 3) basic probability assignment 4) attribute aggregation, 5) Combined degree of belief calculation, 6) utility function 7) ranking

2.1 INFORMATION ACQUISITION AND REPRESENTATION

One of the critical tasks of developing a decision system is to acquire information and to represent them in appropriate format so that it will feed into a model. Since ER approach employs belief structure to acquire knowledge, appropriate information should be selected to feed the ER algorithm, which is used to process the information.

Let **Location of healthcare center**(S) be an attribute at level 1 as shown in Figure 1, which is to be assessed for an alternative(A)(i.e. a hospitals at a certain location) and this assessment can be denoted by A(S). This is to be evaluated based on a set of w_i sub-attributes (such as Environment and safety, size, cost effectiveness) at level 2, denoted by: $S = \{w_1, w_2, w_3, \ldots\ldots\ldots\ ..w_i, \ldots.. w_n\}$.

Location of healthcare center(S) can be assessed by using a set of evaluation grades consisting of Excellent (H_1), Good (H_2), Average (H_3), Bad (H_4)and this set can be written as $H=\{H_1,H_2,\ldots\ldots.H_n;n=1,2,\ldots\ldots,N\}$. These evaluation grades are mutually exclusive and collectively exhaustive and hence, they form a frame of discernment in D-S terminology.

A degree of belief is associated with each evaluation grade, which is denoted by $\{(H_n, \beta_n), n = 1,\ldots\ldots, N\}$ Hence, $A(S) = \{(H_n, \beta_n), n = 1,\ldots\ldots, N\}$ denotes that the top attribute S is assessed to grade $H_n$with the degree of belief β_n. In this assessment, it is required that $\beta_n \geq 0$ and $\sum_{n=1}^{N} \beta_n \leq 1$. If $\sum_{n=1}^{N} \beta_n = 1$ the assessment is said to be complete and if it is less than one then the assessment is considered as incomplete. If $\sum_{n=1}^{N} \beta_n = 0$ then the assessment stands for complete ignorance. In the same way, sub-attribute w_i is assessed to grade H_n with the degree of belief $\beta_{n,i}$ and this assessment can be represented as

$A(w_i) = \{(H_n, \beta_{n,i}), n = 1,\ldots\ldots, N \quad and \quad i = 1,\ldots\ldots, n\}$ Such that $\beta_{n,i} \geq 0$ and $\sum_{n=1}^{N} \beta_n \leq 1$.

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.

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

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. The ER algorithm, as will be discussed, has the procedures to handle such kind of ignorance. It is also necessary to distribute the degree of belief between evaluation grades for certain quantitative input data. For example, sub-attribute**Parking Space** which is at the level 3 of the Figure 1, consists of four evaluation grades namely Excellent, Good, Average and Bad. When the hospital parking space is 50000 square feet, it is considered as excellent, when it is 40000 square feet it is considered as good, when it is 30000 square feet it is considered as average and when it is 20000 square feet it is considered as bad.

However, when hospital parking space is 44000 square feet, it can be both excellent and good. However, it is important for us to know, with what degree of belief it is excellent and with what degree of belief it is good. This phenomenon can be calculated with the following formula.

$$\beta_{n,i} = \frac{h_{n+1} - h}{h_{n+1}, i - h_{n,i}}, \beta_{n+1,i} = 1 - \beta_{n,i} \; if \qquad h_{n,i} \leq h \;\; \leq h_{n+1,i} \ldots\ldots\ldots(2)$$

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. The value of h_{n+1} is related to good. Hence, applying equation (2) the distribution of the degree of belief with respect to hospital parking space is 44000 square feetand the result is given below:

{(Excellent, 0.4), (Good, 0.6), (Average, 0), (Bad,0)},

2.2. WEIGHT NORMALIZATION

The identification of the importance of the attributes is very important, since each attribute does not play the same role in decision making process. For example, the sub-attribute of the "**risk**" attribute at level 2 consists of three attributes namely, Land risk, Construction riskand Timeframe and delivery speed. It is important for us to know among three attributes which is the most important in evaluating their parent attribute "**risk**". This can be carried out by employing different weight normalization techniques such as Eigenvector, AHP, Pair wise comparison [8][9][16][17]. In this research Pair wise comparison method has been considered for the normalization of the weights of the attribute by considering the following equations

.. $\omega_i = \frac{y_i}{\sum_{i=1}^{j} y_i}$;i= 1……j……(3) $\sum_{i=1}^{L} \omega_i = 1$ ……(4)

Equation (3) is used to calculate the importance of an attribute (w_i). This has been calculated by dividing the importance of an attribute (y_i) (this important of the attribute has been determined from survey data) by thesummation $\sum_{i=1}^{j} y_i$ of importance of all the attributes. Equation (4) has been used to check whether the summation of the importance of all the attributes is within one i.e whether they are normalized.

2.3. BASIC PROBABILITY ASSIGNMENT

The degrees of belief as assigned to the evaluation grades of the attributes need to be transformed into basic probability masses. Basic probability mass measures the belief exactly assigned to the n-th evaluation grade of an attribute. It also represents how strongly the evidence supports n-th evaluation grade (H_n) of the attribute. The transformation can be achieved by combining relative weight (w_i) of the attribute with the degree of belief $(\beta_{n,i})$ associated with n-th evaluation grade of the attribute, which is shown by the following equation

$$m_{n,i} = m_i(H_n) = w_i \beta_{n,i}(a_l), ,, n = 1, \ldots\ldots N; ,, i = 1, \ldots\ldots\ldots, L, \quad \ldots\ldots(5)$$

However, in case of hierarchical model, the basic probability mass represents the degree to which the i-th basic attribute supports the hypothesis that the top attribute y is assessed to n-th evaluation grade.

The remaining probability mass unassigned to any individual grade after the i-th attribute has been assessed can be given using the following equation.

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w \sum_{n=1}^{N} \beta_{n,i}(a_l), \quad i = 1, \ldots\ldots\ldots, L, \quad \ldots\ldots(6)$$

2.4. ER ALGORITHM (KERNEL OF ER APPROACH)

The purpose of ER algorithm is to obtain the combined degree of belief at the top level attribute of a hierarchy based on its bottom level attributes, also known as basic attributes. This is achieved through an effective process of synthesizing/aggregating of the information. A recursive ER algorithm is used to aggregate basic attributes to obtain the combined degree of belief of the top level attribute of a hierarchy, which can be represented as $A(S) = \{(H_n, \beta_n), n = 1, \ldots\ldots, N\}$. In this recursive ER algorithm, all the basic attributes are aggregated recursively in the following manner as shown in Figure. 2.

In this Figure.2 "**risk**" is considered as the top level attribute, which consists of three sub-attributes. The top level attribute "risk" can be denoted by w (i) such that i= 1, 2, 3,..n. This means at this level there could be other attributes. For example, in our case, this level consists of five attributes and the level is considered as second level as shown in Figure. 1. It is interesting to note that top level of Figure.1 contains only one attribute and that can be denoted by S (**Location of healthcare center**) and has five sub-attributes at second level. For the top level attribute (S) the combined degree of belief needs to be calculated based on the second level attributes.

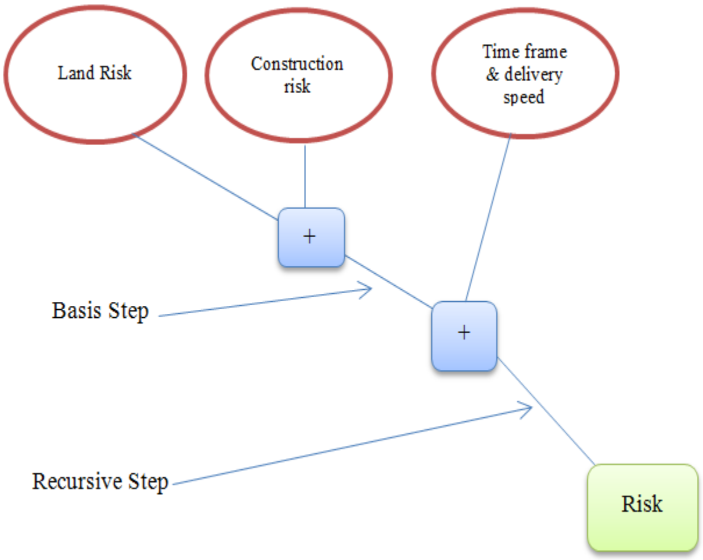

Figure.2 Recursive Manner of Assessment

From Figure.2 it can be observed that w(1), [considering the value of i as 1] consists of three sub-attributes and hence $w_1 = \{w_{11}, w_{12}, w_{13}\}$ or $w(i) = \{w_{i,j}, w_{i,j+1}, w_{i,J+2}, \ldots\ldots\ldots \ldots w_{i,J+n}\}$ such that i=1…..n and j = 1…..L. Taking account of the basic probability assignment and remaining unassigned probability mass of eight sub-attributes mass of W_1 matrix (1) has been developed as shown below. These bpa (such as m_{11}, m_{21},,etc and reaming unassigned bpa such M_{H1}) have been calculated by using equations 5 and 6.

$$M = \begin{bmatrix} m_{11} & m_{21} & m_{31} & m_{41} & m_{H1} \\ m_{12} & m_{22} & m_{32} & m_{42} & m_{H2} \\ m_{13} & m_{23} & m_{33} & m_{43} & m_{H3} \\ m_{14} & m_{24} & m_{34} & m_{44} & m_{H4} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ m_{18} & m_{28} & m_{38} & m_{48} & m_{H8} \end{bmatrix} \ldots. (1)$$

$$M = \begin{bmatrix} m_{1I(2)} & m_{2I(2)} & m_{3I(2)} & m_{4I(2)} & m_{HI(2)} \\ m_{13} & m_{23} & m_{33} & m_{43} & m_{H3} \\ m_{14} & m_{24} & m_{34} & m_{44} & m_{H4} \\ m_{15} & m_{25} & m_{35} & m_{45} & m_{H5} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ m_{18} & m_{28} & m_{38} & m_{48} & m_{H8} \end{bmatrix} \ldots\ldots.(2)$$

From matrix (1), it can be seen that each sub-attribute is associated with five basic probability assignment(bpa), where four first four bpa $(m_{11}, m_{21}, m_{31}, m_{41})$ are associated with four evaluation grades (H_1, H_2, H_3, H_4) and final bpa i.e. $m_{H,i}$ is showing the remaining probability mass unassigned to any individual grades after the assessments on sub-attribute have been considered. Each row in this matrix represents bpa related to one basic attribute or sub-attribute.

Now it is necessary to aggregate the bpa of different sub-attributes. The aggregation is carried out in a recursive way. For example, the bpa of first sub-attribute attribute (which is shown in the first row of the matrix 1) is aggregated with thebpa of second sub-attribute. The result of this aggregation is illustrated in the first row of the matrix (2) and this can be considered as the base case of this recursive procedure since this will be used in the latter aggregation of the sub-attributes. This aggregation can be achieved by using the following equation, which will yield combined bpa (such as $m_{1I(2)}, \ldots\ldots\ldots \ldots. m_{4I(2)}$) as shown in the first row of the second matrix.

$$m_{1I(2)} = K_{I(2)}(m_{11}m_{12} + m_{H1}m_{12} + m_{H2}m_{11}) \quad \ldots\ldots\ldots\ldots(7)$$

Similarly $m_{2I(2)}, m_{3I(2)}, m_{4I(2)}$ can be calculated.

Where $K_{I(2)}$ is a normalization factor used to resolve the conflict and this can be calculated using the equation (8).

$$K_{I(i+1)} = \left[1 - \sum_{n=1}^{N} \sum_{\substack{t=1 \\ t \neq n}}^{N} m_{n,I(i)} m_{t,i+1} \right]^{-1}, i = 1, \ldots\ldots, L-1 \ldots\ldots\ldots\ldots(8)$$

The aggregation of the third attribute is carried out with the resultant of the aggregation of the bpa of the first two attributes. In this way, the aggregation of the other attributes is carried out and finally, the combined aggregations of all the attributes are obtained. This phenomenon has been depicted in Figure 2, where the combined aggregation is obtained, which will be used to obtain the combined degree of belief for the second level attribute "**risk**". Equation (9) represents the more generalized version of equation (7)

$\{H_n\}$:

$$m_{n,I(i+1)} = K_{I(i+1)} \left[m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} + m_{H,I(i)} m_{n,i+1} \right] \ldots\ldots\ldots(9)$$

$$m_{H,I(i)} = \overline{m}_{H,I(i)} + \tilde{m}_{H,I(i),} \quad n = 1, \ldots\ldots\ldots, N, \ldots..(10)$$

$\{H\}$:

$$\tilde{m}_{H,I(i+1)} = K_{I(i+1)} \left[\tilde{m}_{H,I(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)} \overline{m}_{H,i+1} + \overline{m}_{H,I(i)} \tilde{m}_{H,i+1} \right] \ldots\ldots.(11)$$

$$\{H\} : \overline{m}_{H,I(i+1)} = K_{I(i+1)} \left[\overline{m}_{H,I(i)} \overline{m}_{H,i+1} \right], \ldots\ldots.. (12)$$

Equation 13 is used to calculate the combined degree of belief by using final combined basic probability assignment, say in this case "**risk**".

$$\{H_n\} : \beta_n = \frac{m_{n,I(L)}}{1 - \overline{m}_{H,I(L)}}, n = 1, \ldots\ldots\ldots, N, \ldots\ldots\ldots(13)$$

$$\{H\} : \beta_H = \frac{\tilde{m}_{H,I(L)}}{1 - \overline{m}_{H,I(L)}}, \text{Where } m_{n,I(1)} = m_{n,1} (n = 1, \ldots.. N) \ldots.(14)$$

β_n and β_H represent the belief degrees of the aggregated assessment, to which the general factor (such as "**risk**") is assessed to the grade H_n and H, respectively. The combined assessment can be denoted by $S(y(a_l)) = \{(H_{n,} \beta_n(a_l)), n = 1, \ldots\ldots, N\}$, . It has been proved that $\sum_{n=1}^{N} \beta_n + \beta_H = 1$

The recursive ER algorithm combines various piece of evidence on a one-by-one basis.

2.5 THE UTILITY FUNCTION (RANKING LOCATION)

Utility function is used to determine the ranking of the different alternatives. In this research hospital at five locations have been considered as the alternatives. Therefore, the determination of ranking of the alternatives will help to take a decision to decide the suitable location of a hospital. There are three different types of utility functions considered in the ER approach namely: minimum utility, maximum utility and average utility. In this function, a number is assigned to an evaluation or assessment grade. The number is assigned by taking account of the preference of the decision maker to a certain evaluation grade. Suppose the utility of an evaluation grade H_n is $u(H_n)$, then the expected utility of the aggregated assessment $S(y(a_l))$ is defined as follows: $u(S(y(a_l))) = \sum_{n=1}^{N} u(H_n) \beta_n(a_l)$

The belief degree $\beta_n(a_l)$ represents the lower bound of the likelihood that a_l is assessed to H_n, whilst the corresponding upper bound of the likelihood is given by $(\beta_n(a_l) + \beta_H(a_l))$ The maximum, minimum and average utilities of a_l can be calculated by:

$$u_{\max}(a_l) = \sum_{n=1}^{N-1} \beta_n(a_l) u(H_n) + (\beta_N(a_l) + \beta_H(a_l)) u(H_N)),$$

$$u_{\min}(a_l) = (\beta_1(a_l) + \beta_H(a_l)) u(H_1) + \sum_{n=2}^{N} \beta_n(a_l) u(H_n),$$

$$u_{average}(a_l) = \frac{u_{\max}(a_l) + u_{\min}(a_l)}{2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

It is important that if $u(H_1)=0$, then $u(S(y(a_l)))=u_{\min}(a_l)$ if all the original assessments $S(e_i(a_l))$ in the belief matrix are complete, then $\beta_H(a_l)=0$ and $u(S(y(a_l)))=u_{\min}(a_l)=u_{\min}(a_l)=u_{average}(a_l)$.
It has to be made clear that the above utilities are only used for characterizing a distributed assessment but not for the aggregation of factors.

III. Results and discussion

In the previous section, we have discussed about the ER method and how to implement it. Therefore, in this section we will look at the results from using this method on the Location of healthcare center in Chittagong [24]. It is however, difficult to find the perfect area to build in without thorough research of the neighborhoods in the city. The ER approach for findingLocation of hospitalconsists mainly of four key parts, which are the identification of factors, the ER distributed modeling framework for the identified factors, the recursive ER algorithms for aggregating multiple identified factors, and the utility function [3] based ER ranking method which is designed to compare and rank alternatives/options systematically. Each part will be described in detail in this section. Location of healthcare center can be described in two broad categories: the Objective attribute, and subjective attribute as shown in Figure. 1 and each attribute weights are
w11=0.11,w12=0.04,w13=0.12,w21=0.02,w22=0.02,w23=0.01,w31=0.02,w32=0.01,w33=0.01,w41=0.02,w42 =0.12,w51=0.14,w52=0.30,w53=0.15

Table 1shows 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.

Table 1Assessment scores of health care location based on sub criteria(E-Excellent,G-Good,A-Average,B-Bad)

Attributes	**Highway Road**	**Kandirpar**	**Racecourse**
Security ward around	**B(0.2)A(0.8)**	**G(0.4)E(0.6)**	**G(0.4)E(0.6)**
Vandal Proof	G(0.4)E(0.6)	B(0.2)A(0.8)	B(0.2)A(0.8)
Open Location	B(0.2)E(0.8)	A(1.0)	G(1.0)
Expansion Capacity	E(1.0)	G(1.0)	G(0.4)E(0.6)
Parking Space	G(1.0)	B(0.2)E(0.8)	E(1.0)
Storey Numbers	B(0.2)A(0.8)	G(0.4)E(0.6)	G(0.4)E(0.6)
Neutral Location	G(0.4)E(0.6)	B(0.2)A(0.8)	B(0.2)A(0.8)
Traffic Access	B(0.2)E(0.8)	A(1.0)	G(1.0)
Public Transport Link	G(1.0)	B(0.2)E(0.8)	E(1.0)
Construction Cost	B(0.2)A(0.8)	G(0.4)E(0.6)	G(0.4)E(0.6)
Land Cost	G(0.4)E(0.6)	B(0.2)A(0.8)	B(0.2)A(0.8)
Land Cost	G(0.4)E(0.6)	B(0.2)A(0.8)	B(0.2)A(0.8)
Land Risk	B(0.2)E(0.8)	A(1.0)	G(1.0)
Construction Risk	E(1.0)	G(1.0)	G(0.4)E(0.6)
Time Frame and delivery Speed	B(0.2)E(0.8)	A(1.0)	G(1.0)

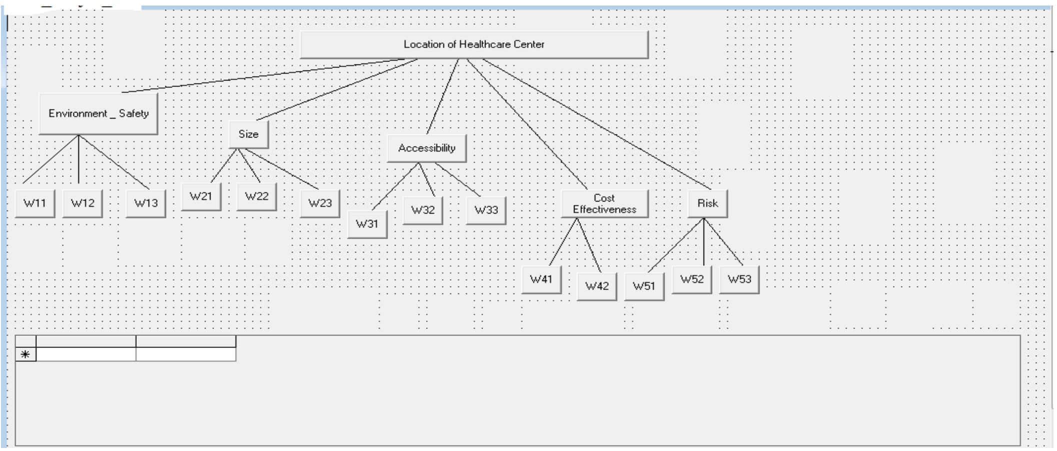

Figure 2. KDSS

Table 2. The Overall Assessment (Alternatives)(DoB-Degree Of Belief)

Alternative	*Excellent*	*Good*	*Average*	*Bad*	*Total DoB*
Highway Road	0.80	0.10	0.10	0.00	1.00
Kandirpar	0.15	0.45	0.20	0.20	1.00
Racecourse	0.18	0.52	0.10	0.20	1.00

*Table 3.*Overall assessment for suitable location

Alternatives	***Expected Utility Score/* ER System Result**	**Manuel Result**	**Benchmark Result**	**Rank**
Highway Road	87%	83%	90%	1
Kandirpar	76%	74%	78%	3
Racecourse	81%	80%	85%	2

The three alternatives (location) simulated data set with assessment outcome is presented in table 3. This table represents overall assessment outcome from location information. The result of this system is measured in percentage for recommendation. The output of this system was generated based on output utility equation (15). In this paper, the utility score of 87% assigned to 'Rank 1', 81% assigned to 'Rank 2' and 72% assigned to 'Rank 3' .

In the case study, the location assessment of three alternatives using this system, manual system and benchmark result is shown in table 3. The historical results were considered as benchmark. From table 3 it can be observed that KDSS generated result has less deviation than from benchmark result. Hence, it can be argued that KDSS output is more reliable than manual system. Therefore, it can be concluded that if the assessment of suitable location evaluation is carried out by using the KDSS, eventually this will play an important role in taking decision to avoid uncertainty issue.

The possible expected utilities of each alternative generated by the KDSSbased on the given utility values for each rank above .The alternatives ranked based on the expected utility. The ranking of alternatives is as follows:

Highway Road>Racecourse>Kandipar

IV. Conclusion

This paper introduced an application of evidential reasoning to solve a MCDA hospital location selection problems with uncertain, incomplete, imprecise, and/or missing information. From the results shown above, it is reasonable to say that the evidential reasoning method is a mathematically sound approach towards selecting thesuitable location as it employs a belief structure to represent an assessment as a distribution. Hence, the ER method can handle a new attribute without recalculating the previous assessment because the attribute can be arranged or numbered arbitrarily which means that the final results do not depend on the order in which the basic attributes are aggregated. Furthermore, any number of new location can be added to the assessment as it does not cause a 'rank reversal' as in the conventional method [8][9][13[14]. Finally, in a composite assessment as in the suitable location selection appraisal which involved objective and subjective assessments of many basic attributes as shown in Figure 1, it is convenient to have an approach which can tackle the uncertainties or incompleteness in the data gathered. Therefore, the ER is seen as feasible method for performance appraisal.

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