Sensitivity Analysis of Multi-Attribute Decision Making Methods in Clinical Group Decision Support System

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***Abstract*- A development of a Clinical Group Decision Support System (CGDSS) has been carried out for diagnosing both neurosis and personality disorders. The knowledge, stored in the knowledge base, were generated from the aggregated preferences given by decision makers. Two types of preferences used here, i.e. the preferences of a mental evidence by a mental condition; and the preferences of a mental disorder by mental condition. Ordered Weighted Averaging operator was adopted to aggregate those preferences. This aggregation process was carried out after transforming the selected subset to fuzzy preference relation format. Then the Bayesian theorem was adopted to compute the probability of evidence given a particular disorder. After developing the knowledge base, the next step is to develop an inference engine. The method used for developing an inference engine is Multi-Attribute Decision Making concept, this is because of the system was directed to choose the best disorder when a particular condition was given. Many methods have been developed to solve MADM problem, however only the SAW, WP, and TOPSIS were appropriate to solve problem here. In this knowledge base, the relation between each disorder and evidence were represented X matrix (m x n) that consist of probability value. Where the X_{ij} was probability of jth mental evidence given i^{th} mental disorder; i=1,2,...,m; and j=1,2,...,n. Sensitivity analysis process was to compute the sensitivity degree of each attribute to the ranking outcome in each method. The sensitivity analysis was aimed to determine the degree of sensitivity of each attribute to the ranking outcome of each method. This degree implies that there were a relevant between an attribute and a ranking outcome. This relevant attribute can be emitted by influence degree of attribute C_j to ranking outcome f_j. Then, relation between sensitivity degree and influence degree for each attribute, can be found by computing the Pearson's correlation coefficient. The biggest correlation coefficient shows as the best result. This research shows that TOPSIS method always has the highest correlation coefficient, and it is getting higher if the change of the ranking is increased. The experimental results shows that that TOPSIS is the appropriate method for the clinical group decision support system for the above purposes.**

Keyword: sensitivity analysis, sensitivity degree, influence degree

I. INTRODUCTION

A knowledge base and an inference engine are the important components of the expert systems. The knowledge base contains the relevant knowledge that is necessary for understanding, formulating, and solving problems, and that is represented in a specific format. The inference process is a part of decision making process that is based on some knowledge stored in the knowledge base. There are many ways to carry out an acquisition knowledge, and to make an inference.

A development of a Clinical Group Decision Support System (CGDSS) has been carried out for diagnosing both neurosis and personality disorders. The knowledge, stored in the knowledge base, were generated from the aggregated preferences given by decision makers. Two types of preferences used here, i.e. the preferences of a mental evidence by a mental condition; and the preferences of a mental disorder by mental condition. Ordered Weighted Averaging (OWA) operator was adopted to aggregate those preferences. This aggregation process was carried out after transforming the selected subset to fuzzy preference relation format. Then the Bayesian theorem was adopted to compute the probability of evidence given a particular disorder. The knowledge base finally consists of a set of probability of given a particular disorder [2].

After developing the knowledge base, the next step is to develop an inference engine. The method used for developing an inference engine is Multi-Attribute Decision Making concept [3], this is because of the system was directed to choose the best disorder when a particular condition was given. Many methods have been developed to solve MADM problem, i.e. Analytical Hierarchy Process (AHP), Simple Additive Weighting (SAW), Weighed Product (WP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [4]. In this research, the SAW and TOPSIS were proved appropriate to solve the problem.

II. RASIONALE

Methods used to solve MADM problems sometime results in different outcome during the exploitation phase. This may become problems for some decision makers. They have difficulties to determine the best alternative solution given by these methods. A sensitivity analysis is necessary to carry out to determine best method. The most sensitive analysis shows the best method. In this research, we will do sensitivity analysis to 3 MADM methods, i.e. SAW and TOPSIS to determine what method that appropriate to my clinical group decision support system (CGDSS).

III. METHODOLOGY

In this knowledge base, the relation between each alternative (disorder) and attribute (evidence) is represented as the X matrix (m x n) which consists of probability values, where the X_{ij} is the probability of j^{th} mental evidence given i^{th} mental disorder; i=1,2,...,m; and j=1,2,...,n. A sensitivity analysis process will carried out by computing the sensitivity degree of each attribute, and by ranking the outcome in each method (SAW and TOPSIS). This algorithm will compute the sensitivity degree (s_j) of each attribute (developed from Chung-Hsing [1]):

1. Assign all attributes a weight value of 1, called basic weight (j = 1, 2, ..., attribute number that support a particular knowledge);
2. Change the weight for the attribute in the range between 1 and 2, with an increment of 0.1, while all attributes are kept at their basic weights.
3. Normalize the modified attribute weights to satisfy $\Sigma w = 1$.
4. Apply the method having the weights obtained at step (3).
5. Compute the percentage of the changes of the ranking, and compares to the ranking outcome with equal weight.

Here, the sensitivity analysis is aimed to determine the degree of sensitivity of each attribute to the outcome ranking of each method. This degree implies that there is a relevant between an attribute and an outcome rank. This relevant attribute can be emitted by influence degree of attribute C_j to outcome rank f_j (developed from [1]):

$$f_j = \frac{d_j}{\sum_{k=1}^{n} d_k}; \quad (1)$$

j = 1, 2, ..., attribute number that support a particular knowledge.

where:

$$d_j = 1 + h\sum_{i=1}^{m} p_{ij} \ln(p_{ij}); \quad (2)$$

j = 1, 2, ..., attribute number that support a particular knowledge.

$$p_{ij} = \frac{x_{ij}}{\sum_{k=1}^{m} x_{kj}}; \quad (3)$$

i=1,2,..., alternative number.

$$h = \frac{1}{\ln(m)} \quad (4)$$

Then, relation between sensitivity and influence degrees for each attribute in each method, can be found by computing the Pearson's correlation coefficient. The method which the biggest correlation coefficient is the best one.

In the previous research a knowledge base of clinical GDSS has been built. The knowledge base consists of 135 evidences which influence on 30 disorders. The level of influence of the j^{th} evidence (a_j) on rank outcome, f_j, can be computed by equation 1-4 The result of f_j is shown in the first column of Table 1. For example, the first row (f_1 = 0.00359) indicates that given 30 disorders, 135 evidences, the relative influence on the first evidence of the rank outcome is 0,00359. The matrix X that consists relation between each disorder and each evidence is tabulated in Table 1, Using 135 evidences, the higher number of the relative influences are the 23^{rd}, 24^{th}, 25^{th}, 27^{th}, 32^{nd}, 54^{th}, 56^{th}, 58^{th}, 59^{th}, 60^{th}, 65^{th}, 67^{th}, 70^{th}, 86^{th}, 119^{th}, 122^{nd}, 123^{rd}, 125^{th}, 126^{th}, 128^{th}, 129^{th}, 130^{th}, 131^{st}, 132^{nd}, 133^{rd}, 134^{th}, and 135^{th}. Otherwise, the value of the 4^{th} relative influence is the lowest one.

TABLE I
THE LEVEL OF RELATIVE INFLUENCE (F_I) AND THE LEVEL OF RELATIVE SENSITIVITY (S_J)

The –i^{th} l Symptom	Level of relative influence (f_i)	Level relative sensitivity (s_j)		The change of rank if the –i th symptom weight (w_i) = 1,1; w_j others ($j \neq i$) = 1	
		SAW	TOPSIS	SAW	TOPSIS
1	0.00359	0	0.06667	0	2
2	0.00370	0	0.06667	0	2
3	0.00410	0	0.06667	0	2
4	0.00246	0	0	0	0
5	0.00775	0	0	0	0
6	0.00586	0	0	0	0
7	0.01058	0	0	0	0
8	0.00458	0	0	0	0
9	0.00601	0	0	0	0
10	0.00357	0	0	0	0
11	0.00353	0	0	0	0
12	0.00654	0	0	0	0
13	0.00357	0	0	0	0
14	0.00555	0	0.06667	0	2
15	0.00462	0	0.06667	0	2
16	0.00436	0	0.06667	0	2
17	0.01005	0.06667	0.06667	2	2
18	0.00498	0	0	0	0
19	0.00448	0	0	0	0
20	0.00625	0	0	0	0
21	0.00344	0	0	0	0
22	0.00323	0	0	0	0
23	0.01321	0	0	0	0
24	0.01321	0	0	0	0
25	0.01321	0	0	0	0
26	0.00270	0	0	0	0
27	0.01321	0	0	0	0

The $-i^{th}$ l Symptom	Level of relative influence (f_i)	Level relative sensitivity (s_j)		The change of rank if the $-i^{th}$ symptom weight (w_i) = 1,1; w_j others ($j \neq i$) = 1	
		SAW	TOPSIS	SAW	TOPSIS
28	0.00379	0	0	0	0
29	0.00426	0	0.06667	0	2
30	0.00597	0	0	0	0
31	0.00598	0	0	0	0
32	0.01321	0	0.06667	0	2
33	0.00451	0	0.06667	0	2
34	0.01052	0	0.06667	0	2
35	0.01026	0.06667	0.06667	2	2
36	0.00724	0	0	0	0
37	0.00724	0	0	0	0
38	0.00704	0	0	0	0
39	0.00936	0.06667	0.06667	2	2
40	0.00944	0.06667	0.06667	2	2
41	0.00966	0.06667	0.06667	2	2
42	0.00866	0	0	0	0
43	0.01041	0.06667	0.06667	2	2
44	0.00615	0.06667	0.06667	2	2
45	0.00585	0.06667	0.06667	2	2
46	0.00742	0.06667	0.06667	2	2
47	0.00656	0.06667	0.06667	2	2
48	0.00524	0.06667	0.06667	2	2
49	0.00718	0.06667	0.06667	2	2
50	0.01174	0.06667	0.06667	2	2
51	0.01124	0.06667	0.06667	2	2
52	0.00744	0.06667	0.06667	2	2
53	0.00453	0.06667	0	2	0
54	0.01321	0	0	0	0
55	0.00335	0	0	0	0
56	0.01321	0	0.2	0	6
57	0.00618	0.06667	0.06667	2	2
58	0.01321	0	0.1	0	3
59	0.01321	0.06667	0.16667	2	5
60	0.01321	0.06667	0.13333	2	4
61	0.00408	0	0	0	0
62	0.00469	0	0.06667	0	2
63	0.00460	0	0	0	0
64	0.00454	0	0	0	0
65	0.01321	0	0	0	0
66	0.00373	0.06667	0.06667	2	2
67	0.01321	0	0	0	0
68	0.00365	0.06667	0.06667	2	2
69	0.00604	0	0.06667	0	2
70	0.01321	0	0.06667	0	2
71	0.00527	0	0	0	0
72	0.00527	0	0	0	0
73	0.00506	0	0.13333	0	4
74	0.00595	0	0	0	0
75	0.00354	0.06667	0	2	0
76	0.00583	0	0	0	0
77	0.00842	0	0	0	0

The $-i^{th}$ l Symptom	Level of relative influence (f_i)	Level relative sensitivity (s_j)		The change of rank if the $-i^{th}$ symptom weight (w_i) = 1,1; w_j others ($j \neq i$) = 1	
		SAW	TOPSIS	SAW	TOPSIS
78	0.00844	0	0	0	0
79	0.00573	0	0	0	0
80	0.00633	0.06667	0	2	0
81	0.00466	0	0	0	0
82	0.00522	0	0	0	0
83	0.00480	0	0	0	0
84	0.00468	0	0	0	0
85	0.00383	0	0	0	0
86	0.01321	0	0	0	0
87	0.00410	0	0	0	0
88	0.00782	0	0	0	0
89	0.00380	0	0	0	0
90	0.00400	0	0	0	0
91	0.00385	0	0	0	0
92	0.00425	0	0	0	0
93	0.00635	0	0	0	0
94	0.00640	0	0	0	0
95	0.00519	0	0	0	0
96	0.00520	0	0	0	0
97	0.00681	0	0	0	0
98	0.00560	0	0	0	0
99	0.00577	0	0	0	0
100	0.00609	0	0	0	0
101	0.00661	0	0	0	0
102	0.00509	0	0	0	0
103	0.00689	0	0	0	0
104	0.00729	0	0	0	0
105	0.00648	0	0	0	0
106	0.00482	0	0	0	0
107	0.00577	0	0	0	0
108	0.00858	0	0	0	0
109	0.00496	0	0	0	0
110	0.00568	0	0	0	0
111	0.00635	0	0	0	0
112	0.00587	0	0	0	0
113	0.00675	0	0	0	0
114	0.00357	0	0	0	0
115	0.00423	0	0	0	0
116	0.00425	0	0	0	0
117	0.00411	0	0	0	0
118	0.00604	0	0	0	0
119	0.01321	0	0	0	0
120	0.00894	0	0	0	0
121	0.00894	0	0	0	0
122	0.01321	0	0	0	0
123	0.01321	0	0	0	0
124	0.00894	0	0	0	0
125	0.01321	0	0	0	0
126	0.01321	0	0	0	0
127	0.01089	0.06667	0.06667	2	2

The $-i^{th}$ l Symptom	Level of relative influence (f_i)	Level relative sensitivity (s_j)		The change of rank if the $-i^{th}$ symptom weight (w_i) = 1,1; w_j others ($j \neq i$) = 1	
		SAW	TOPSIS	SAW	TOPSIS
128	0.01321	0	0	0	0
129	0.01321	0	0	0	0
130	0.01321	0	0.06667	0	2
131	0.01321	0	0.06667	0	2
132	0.01321	0	0.06667	0	2
133	0.01321	0	0	0	0
134	0.01321	0	0	0	0
135	0.01321	0	0	0	0
Total	**1**	**1**	**1**	**48**	**92**

The second column in Table 1 shows the values of the level of relative sensitivity of the j^{th} evidences (s_j) computed by Simple Additive Weighting (SAW) method. The values on third column in Table 1 shows the values of level relative sensitivity of the j^{th} of evidence (s_j) computed using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The sensitivity degree is computed using the Chung-Hsing algorithm. The 5^{th} and 6^{th} columns show the changes in rank if the values of the i^{th} evidence weights are set on 1.1 and the other values of evidence weights are set as unity. If changes in weight is carried out in the first evidence, there are no changes in rank computed using SAW method. If change in weight is done in the first evidence, there are 2 changes in rank computed using TOPSIS method. By using SAW method, there are totally 48 changes in rank and by using TOPSIS method there are totally 92 changes in rank. The values on the first row and the second column of Table 1 are zeros. This indicates that by using SAW method, setting $w_1 = 1.1$ and setting w_2 until $w_{135} = 1$, there are no changes in rank of disorders. In other word, the rank of disorders, for $w_1 = 1.1$ and for w_2 until $w_{135} = 1$, are the same as the rank of disorder for all weights are unity. In the other hand, the values on the first row and the third column of Table 1 both are 0.06667. These indicate that by using TOPSIS method, setting $w_1 = 1.1$ and setting $w_2 \ldots w_{135} = 1$, causes only 2 changes in rank of disorders.

Next, the correlation coefficient (r) between f_i and s_i is computed for showing the influence on evidence weight of rank outcome. The correlation coefficient is computed based on Pearson method. If a series of n measurements of X and Y is written as x_i and y_i where i = 1, 2, ..., n, then the Pearson product-moment correlation coefficient can be used to estimate the correlation of X and Y. The Pearson coefficient is also known as the "sample correlation coefficient". It is especially important if X and Y are both normally distributed. The Pearson correlation coefficient is then the best estimate of the correlation of X and Y [5][6]:

Using the Pearson correlation coefficient, the correlation coefficients are 0.087 applied on SAW method and 0.23375 on TOPSIS method. These values are small enough, because there are many evidences that influence on some different disorders. The correlation coefficient applied on TOPSIS method is greater than that is applied on SAW method. This means that TOPSIS method will be chosen as inference method if this system accomodates 135 evidences and 30 disorders.

REFERENCES

[1] Chung-Hsing, Yeh. 2002. *A Problem-based Selection of Multi-Attribute Decision Making*. International Transaction of Operational Research, vol 9, pp:169-181.

[2] Kusumadewi, Sri, and Hartati, Sri. 2007. *Utilizing Fuzzy Multi-Attribute Decision Making for Group Clinical Decision Making Model*. SITIA, ITS, Surabaya.

[3] Kusumadewi, Sri; Hartati, Sri; Wardoyo, Retanto; and Harjoko, Agus. 2007. *Fuzzy Multi-Attribute Decision Making*. Graha Ilmu, Yogyakarta.

[4] Janko, Wolfgang. 2005. *Multi-Criteria Decision Making: An Application Study of ELECTRE & TOPSIS*.

[5] David. 2007. "Pearson's Correlation". Online pada http://davidmlane.com/hyperstat/ A51911.html, diakses April 2007.

[6] Wikipedia. 2007. "Correlation". http://en.wikipedia.org/wiki/ Correlation, diakses April 2007.