

Utilizing Fuzzy Multi-Attribute Decision Making for Group Clinical Decision Making Model

Sri Kusumadewi¹, Sri Hartati²
cicie@fti.uii.ac.id , shartati@ugm.ac.id

1. Informatics Department
 Faculty of Industrial Technology
 Indonesia Islamic University, Yogyakarta

2. Electronic and Instrumentation Lab., Computer Science Department
 Faculty of Mathematic and Natural Sciences
 Gajah Mada University, Yogyakarta

Abstract

This research is aimed to build a Clinical Group Decision Support System model that is used to diagnose the mental disorder. This model makes use of the experts' competence to give their preferences for some features related with the kinds of mental disorder. The knowledge base is built based on those preferences through preference aggregation process using Fuzzy Multi-Attribute Decision Making (FMADM) steps. Aggregation process is used to make selection of some feature in a group of features and to make selection of the best alternative in a group of alternatives. Ordered Weighted Averaging (OWA) operator is used to do this feature preference aggregation. Importance Induced Ordered Weighted Averaging (I-IOWA) operator is used to do this alternative preference aggregation. Then Quantifier Guided Dominant Degree (QGDD) operator is used to determine the relevant features and the most possible kind of mental disorder. The inference process is used to diagnose the patient. Bayesian Belief Networks (BBN) is used to do the diagnosis process. Conditional probability is given from knowledge base and patient condition. This research has already been used to solve a CDSS case with 5 decision makers, 30 disorders, and 124 features. Finally, we have 635 knowledges in knowledge base.

Keywords: *Clinical Group Decision Support, Fuzzy Multi-Attribute Decision Making, preference*

1 Introduction

The problem in decision making is often faced by some organization e.g. industrial, military, banking, medical circles and other organization. Parts of this problem are aimed to select a group of alternatives by considering some criteria. The decision making process is very easy if the alternative choices is only based on criterion. If there are a lot of criteria where each alternative has certain value, it will be needed an aggregation method to get a single value for each alternative. In the decision making system, this problem will be solved in Multi Criteria Decision Making (MCDM). The study of MCDM had been known at the end of the 19th century. Its rapid development, however, had been felt since 1970s, especially in the operation research circle [1][2].

In its development, the MCDM researchers focus on how to model computation if the decision maker gives his preferences both to some alternatives and some criteria. The decision makers usually give their preferences numerically in order to make the computation easier. The fuzzy logic is the most effective one to be used to solve MCDM problems which the given data is ambiguous or they are represented linguistically [3][4]. Researchs about fuzzy

MCDM have been done and published in some journals [5][6][7][8][9][10].

On the other side, knowledge in the medical domain has improved in the last decade, a lot of information comes to doctors. This situation, is predicted, continuously increases doubled every 20 year [11]. The surveys have shown that the use of computer for Clinical Decision Support System (CDSS) in the last 20 years can economize the total cost up to less than 5% compared with the computer usage before [12].

Some researches have developed expert systems in the psychiatry domain. Pichot classified the diagnosis in the psychiatry circle with probability method [13][14]; Heiser and Brooks built HEADMED system to psychotic threatment [15]; Werner built an expert system to geriatric psychiatri [16]; McWilliam developed AGECA system [17]; Portelli develop an expert system to Franch nosography [18]; Plugge built an expert system to dementia diagnosis, called EVINCE-1 [19]; and and Ohayon develop an expert system to multicentric psychopharmacology, called ADINFER [20]. All systems mentioned above have not accommodated a decision making in group.

Mental disorder patient normally is treated more than one doctors, therefore it is really needed a system that can accommodate doctor' preferences to aid diagnosing. Here a model for clinical group decision making has been built in this research. Its knowledge base is acquired based on the experts' preferences using fuzzy multi-attribute decision making (FMADM) concept. An alternative of diagnosis of mental disorder then is handled by this model and will be implemented as Clinical Group Decision Support System (CGDSS).

2 Clinical Group Decision Support System (CGDSS) Structure

The system being to built is CGDSS, that focuses on diagnose of neurosis, somatoform, stress and personality disorder following them. Commonly, the clinical decision support system diagram is shown in Figure-1. This system consists of decision maker group, they are psychiatrist and clinical psychologist who take part in building the knowledge base. It consists of some regulations to determine the category of the disorder in neurosis, somatoform, stress and personality disorder following them. It also consists of some therapy alternatives for them. This group is led by the group leader as the coordinator..

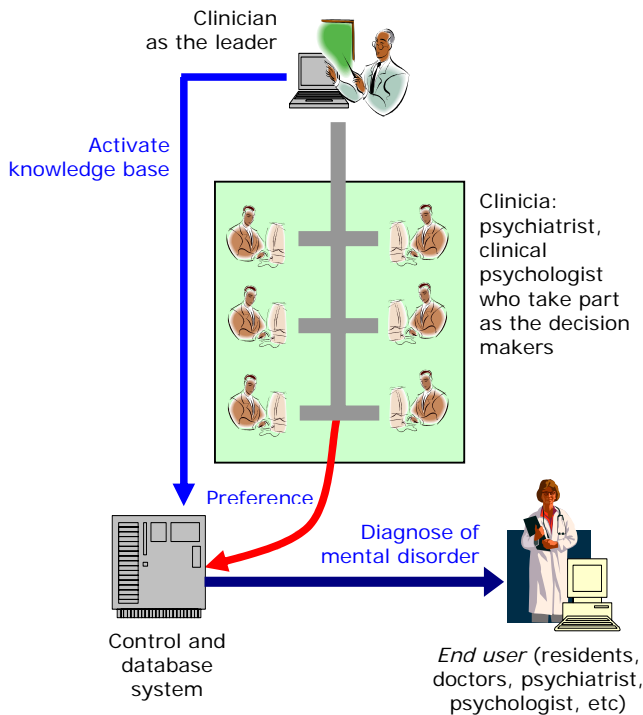


Figure 1. Structure of CDSS system.

2.1 Target user

The system has following user target:

- a. The experts. They are psychiatry, clinical psychologist who will take part in giving their preferences to complete the regulation in the knowledge base.
- b. The residents (the university student in the last semester who help the doctor), community health

centre or local hospital (both general hospital and hospital for mentally disorder people) as the end users to make a diagnose to the patient.

2.2 CDSS Category

The CDSS mentioned above is the solicited advice which will only give its advice if the system is instructed to give the advice. The users (psychiatrists, psychologist, the residents and the other users) can consult with DSS explicitly.

2.3 Decision Support Model

Decision support model used in this system utilizes the expert system concept, so the formation of knowledge base and inference mechanism are absolutely needed. Integration between quantitative method and qualitative method is applied to build this expert system.

2.4 Formation of The Knowledge Base

This system consists of a set of decision makers, $E = \{e_1, \dots, e_R\}$, a set of alternatives, $A = \{a_1, \dots, a_m\}$, and a set of features, $C = \{c_1, \dots, c_n\}$. Each decision maker can give contribution to create a set of feature supporting a condition of knowledge. For an example, e_1 gives a set of features supporting the first knowledge (R_1) as: c_1 and c_3 and c_{10} and c_{13} . The other decision makers can give his preferences to a set of features corresponding on the condition. Utility format is used to represent those preference, as $U^k = (u_1^k, u_2^k, \dots, u_t^k)$ where $u_i^k \in [0,1]$; $1 \leq i \leq t$ and u_i^k is utility given by decision maker e^k on feature C_i , $i=1,2,\dots,t$, in particular condition. Each preference that represents an importance degree will transform to fuzzy preference relation as [21]:

$$p_{ij}^k = \frac{(u_i^k)^2}{(u_i^k)^2 + (u_j^k)^2}; \quad 1 \leq i \neq j \leq m \quad (1)$$

where u_i^k is a preference given by e_k on feature C_i di U^k , $i=1,2,\dots,t$.

If some decision makers have given their preferences, then *Ordered Weighted Averaging (OWA)* operator is used to compose those preferences. OWA operator from n dimensional functions, $\phi : \mathfrak{R}^n \rightarrow \mathfrak{R}$, corresponding on a set of weights or weigh vectors $W = (w_1, \dots, w_n)$ where $w_i \in [0,1]$ and $\sum_{i=1}^n w_i = 1$; used to compose ordered value $\{p_1, \dots, p_n\}$ as:

$$\phi_w(p_1, \dots, p_n) = \sum_{i=1}^n w_i p_{\sigma(i)} \quad (2)$$

to a permutation $\sigma : \{1, \dots, n\} \rightarrow \{1, \dots, n\}$ so that $p_{\sigma(i)} \geq p_{\sigma(i+1)}$, $\forall i = 1, \dots, (n-1)$; $p_{\sigma(i)}$ is the highest value in $\{p_1, \dots, p_n\}$. Finally, exploitation phase is carried out to choose the relevan features in particular condition from a group of features by considering aggregation matrix from the decision

makers. We use Quantifier Guided Dominant Degree (QGDD) to do this. The format of QGDD is:

$$QGDD_i = \phi_Q(p_{ij}^c, j = 1, \dots, n, j \neq i)$$

Figure-2 shows a process of creating condition supporting a knowledge.

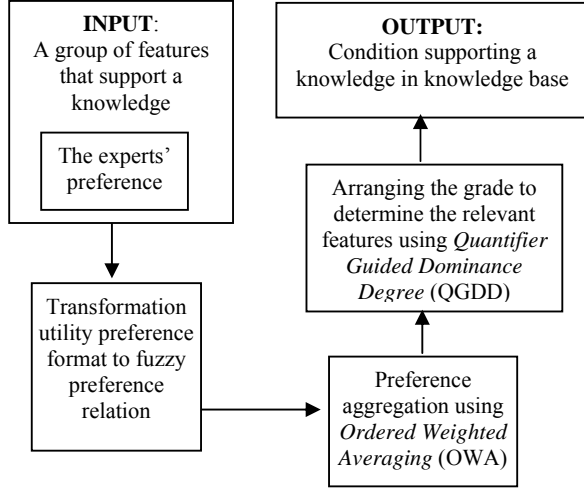


Figure 2. Diagram of creating a condition supporting a knowledge.

After building some conditions supporting some knowledge's, each decision maker gives his preference to a group of alternatives related on particular condition. The preference format is (Ma, 2004):

$$\tilde{A}^k = (A_{i1}^k, A_{i2}^k, \dots, A_{im}^k) \subset A \text{ where } i_m < m.$$

Alternatives in \tilde{A} equivalent and dominated those in left of A . Each preference that represents an importance degree will transform to fuzzy preference relation as:

$$p_{ij}^k = \begin{cases} 1; & A_i \in \hat{A}, A_j \in A / \hat{A}; \\ 0,5; & \text{otherwise} \end{cases}; \quad 1 \leq i \neq j \leq m \quad (4)$$

Having some given their preferences to a group of alternatives, *Importance Induced Ordered Weighted Averaging (I-IOWA)* operator is used to compose those preferences. I-IOWA is the aggregation operator which involves the interest level from the decision makers and is used in heterogeneous group support system. The degree of important can be interpreted as fuzzy subset $\mu_i: E \rightarrow [0, 1]$ so that $\mu_i(e_k) = u_k \in [0,1]$. If the k decision maker gives the preference of alternative x_i to alternative x_j as p_{ij}^k with importance degree u_k , so it is necessary to transform p_{ij}^k to \bar{p}_{ij}^k through the transformation function g as:

$$\bar{p}_{ij}^k = g(p_{ij}^k, u_k) \quad (5)$$

Transformation function g can be the minimum operator (Herrera, 1997), exponential $g(x,y) = x^y$ (Yager, 1978), or it is usually used t-norm operator (Zimmermann, 1991). Yager (1996) had suggested a

procedure to evaluate the overall satisfaction of Q criteria (experts) by the alternative x . In this procedure, once the satisfaction values to be aggregated have been ordered, the weighting vector associated to an I-IOWA operator using a linguistic quantifier Q are calculated following the expression:

$$w_i = Q \left(\frac{\sum_{k=1}^i u_{\sigma(k)}}{T} \right) - Q \left(\frac{\sum_{k=1}^{i-1} u_{\sigma(k)}}{T} \right) \quad (6)$$

where $T = \sum_{k=1}^n \mu_k$ is the total sum of importance

degree, and σ is the permutation is used to produce the ordering of the values to be aggregated. The exploitation phase is carried out to choose the best alternative from a group of alternatives by considering aggregation matrix from the decision makers. The Quantifier Guided Dominant Degree (QGDD) is then used to choose the best alternatives. This process is pictorially shown in Figure-3.

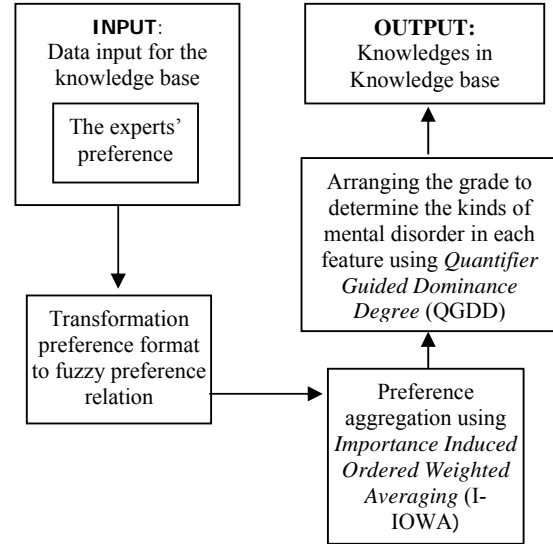


Figure 3. Determining the best disorder for particular condition.

2.5 Diagnosis

After building the knowledge base, the inference mechanism carries out diagnose process according to the features given by the patient. This process determines the kind of mental disorder, such as shown in Figure-4. Bayesian Belief Network (BBN) is used as the method to carry out the diagnose, for the reason that it is enable to the interdependence among some features in the system. BBN defines various events, the dependencies between them, and the conditional probabilities involved in those dependencies. A BBN method uses this information to calculate the probabilities of various possible causes being the actual cause of an event.

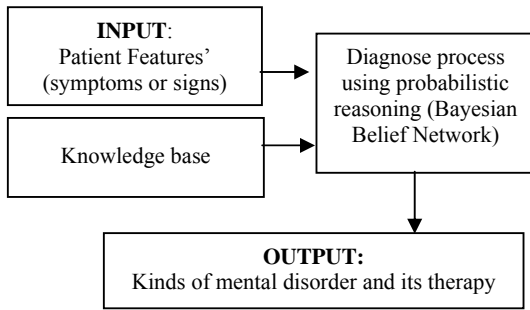


Figure 4. Diagnosis process diagram.

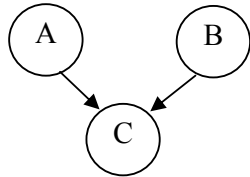


Figure 5. Bayesian network.

For instance, if event C can be effected by events A and B, such as shown in Figure-5. If conditional probabilities of A and B are given by patient, and the other conditional probability given by knowledge base, then probability of C can be calculated as [23]:

$$P(C) = p(C|AB) + p(C|\sim AB) + p(C|A\sim B) + p(C|\sim A\sim B) \quad (6)$$

3 Experiment Result

This system have been being developed and tested. However, this system has tried to solve the clinical group decision support system with 5 decision makers. This case has covered 30 disorders involved in F40.0 – F60.7 from the mental disorder diagnosis guidelines in PPDGJ-III. For example, Table 1 shows some of disorders.

Table 1. The example of disorders.

Code	Disorder name
F40.0	Agoraphobia
F40.1	Social phobia

$$OWA = \begin{pmatrix} 0 & 0.2000 & 0.1000 & 0.0588 & 0.0385 & 0.0270 & 0.0200 \\ 0.8000 & 0 & 0.3077 & 0.2000 & 0.1379 & 0.1000 & 0.0755 \\ 0.9000 & 0.6923 & 0 & 0.3600 & 0.2647 & 0.2000 & 0.1552 \\ 0.9412 & 0.8000 & 0.6400 & 0 & 0.3902 & 0.3077 & 0.2462 \\ 0.9615 & 0.8621 & 0.7353 & 0.6098 & 0 & 0.4098 & 0.3378 \\ 0.9730 & 0.9000 & 0.8000 & 0.6923 & 0.5902 & 0 & 0.4235 \\ 0.9800 & 0.9245 & 0.8448 & 0.7538 & 0.6622 & 0.5765 & 0 \end{pmatrix}$$

Then the QGDD operator (Equation 3) is applied to calculate the QGDD vector. So the QGDD vector of the first condition is:

F40.2	Specific phobia
F41.0	Panic disorder
F41.1	General anxiety disorder

F60.7	Dependent personality disorder

There are 124 fitur (symptoms or signs) involved in these disorders. Table 2 shows some examples of features

Tabel 2. The example of some features (symptoms or signs)

Code	Features
1	Excessive worry, occurring in the crowded situations
2	Avoiding the particular situations
3	Melakukan atau menghadapi situasi tertentu dengan terpaksa
4	Excessive worry, occurring more days than not, for a least six months
5	Inability to control the worry

124	Inability to learn from experiences (especially from a punishment)

A group of features in the first condition is {14, 2, 3, 10, 11, 12, 13}. Each decision makers gives weight of each feature as:

$U^1 = \{3, 5, 1, 3, 3, 1, 1\}$, transformed to utility vector as $U^1 = \{0.6, 1, 0.2, 0.6, 0.6, 0.2, 0.2\}$

$U^2 = \{3, 2, 2, 5, 3, 5, 4\}$, transformed to utility vector as $U^2 = \{0.6, 0.4, 0.4, 1, 0.6, 1, 0.8\}$

$U^3 = \{3, 2, 2, 5, 3, 5, 4\}$, transformed to utility vector as $U^3 = \{0.6, 0.4, 0.4, 1, 0.6, 1, 0.8\}$

$U^4 = \{4, 2, 2, 5, 4, 5, 4\}$, transformed to utility vector as $U^4 = \{0.8, 0.4, 0.4, 1, 0.8, 1, 0.8\}$

$U^5 = \{1, 1, 1, 4, 4, 1, 1\}$, transformed to utility vector as $U^5 = \{0.2, 0.2, 0.2, 0.8, 0.8, 0.2, 0.2\}$

After transforming these utility vectors to fuzzy preference relation (Equation 1), the OWA operator (Equation 2) then is used to aggregate the fuzzy preference relation matrix. So the OWA matrix is:

$$Cond_1 = \{0.1062, 0.4035, 0.5490, 0.6447, 0.7123, 0.7617, 0.7986\}$$

The mean of output QGDD is used as threshold value. In the QGDD vector, if the element less than its

threshold, then its value is setup to 0, this condition indicates that this feature hasn't significantly contribute enough in particular condition. On the contrary, if the element is setup to 1, this condition indicates that this feature has significantly contribute in a particular condition. In this example shows that feature-10, 11, 12, 13 have significantly contribute the first condition.

The mean of $Cond_1$ is 0.5680, so we get:

$$Cond_1 = \{0, 0, 0, 1, 1, 1, 1\}$$

This condition indicates that only {10, 11, 12, 13} features are relevant of the first condition. This process is repeated until all of available conditions are processed. There are 105 conditions already provided 5 decision makers. Table 3 shows part of the output of aggregation preferences to 105 conditions which each of these conditions is involved in a particular knowledge given by 5 decision makers.

Table 3. The example of some conditions.

Condition number	Relevant feature code					
1	10	11	12	13		
2	11	13	15	16		
3	21	22	23	24	25	26
					
105	99	104	106	121	123	

They use selected subset format to select some disorders related to particular condition. Each decision maker give his preference as:

- $A^1 = \{F40.0, F40.2, F41.0, F41.1, F60.0\}$
- $A^2 = \{F40.1, F40.2, F41.0, F41.1, F45.1, F48.1, F32.1, F60.0, F60.6\}$
- $A^3 = \{F40.1, F40.2, F41.0, F41.1, F45.1, F60.0, F60.6\}$
- $A^4 = \{F40.0, F40.2, F41.0, F41.1, F60.0, F60.6\}$
- $A^5 = \{F40.0, F41.0, F41.1, F45.3\}$

After transforming these selected subset vectors to fuzzy preference relation (Equation 4), the I-IOWA operator is utilized (Equation 5-6) to aggregate the fuzzy preference relation matrix. The QGDD operator (Equation 3) then is used to calculate the QGDD vector, and will result in the QGDD vector for the first condition such as:

Knowledge₁ =
 {0.6215, 0.7575, 0.7574, 0.9288, 0.7563,
 0.4422, 0.4422, 0.4422, 0.4422, 0.4422,
 0.4422, 0.4422, 0.4422, 0.4422, 0.4422,
 0.4422, 0.5616, 0.6203, 0.4422, 0.4422,
 0.4422, 0.4422, 0.5565, 0.5565, 0.7574,
 0.4422, 0.4422, 0.4422, 0.6828, 0.4422}

The mean of $Cond_1$ is 0.5319, so the knowledge₁ is:

Knowledge₁ =
 {1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0,
 0, 0, 1, 0}

It's means that the best selected disorder of the first condition are {F40.0, F40.1, F40.2, F41.0, F41.1, F45.1, F45.3, F48.1, F32.1, F60.0, F60.6}. The term knowledge here refers to show the relation of one condition to one element of QGDD disorder vector. Finally, 635 knowledges are stored in knowledge base, such as shown in Table 4. One condition can generate more than one knowledge, and more than one disorder involved in one condition.

Table 4. The example of some knowledges.

Knowledge number	Relevant feature code	Disorder code
1	10 11 12 13	F40.0
2	10 11 12 13	F40.1
6	11 13 15 16	F40.0
	
635	99 104 106 121 123	F60.3

The system has been tested to diagnose a patients. One of patient symptoms codes' are $S = \{11, 13, 23, 24, 25, 50, 55, 90\}$ with conditional probability of each symptom is $P(S_1) = 0.9; P(S_2) = 0.8; P(S_3) = 0.8; P(S_4) = 0.9; P(S_5) = 0.8; P(S_6) = 0.5; P(S_7) = 0.7; \text{ and } P(S_8) = 0.6$. The conditional probabilities shows the dependency between some features, which are calculated from the knowledge base. So, according to Equation (6), the corresponding disorder probabilities are shown in Table 5.

Table 5. The disorder probabilities

No	Code	Disorder	Probability
1	F40.0	Agoraphobia	0.3721
2	F40.1	Social Phobia	0.3822
3	F40.2	Specific Phobia	0.4060
4	F41.0	Panic disorder	0.1464
5	F41.1	Generalized Anxiety Disorder	0.0109
6	F42.0	Predominantly obsessional	0.0246
7	F42.1	Predominantly compulsive acts	0.0105
8	F43.0	Acute stress reaction	0.0595
9	F43.1	Post-traumatic stress disorder	0.0372
10	F44.0	Dissociative amnesia	0.0130
	...		
29	F60.6	Anxious personality disorder	0.5020
30	F60.7	Dependent personality disorder	0.0015

The best probability of those disorders is 0.509, related to F60.6 (Anxious [avoidant] personality disorder).

4 Conclusion and Future Work

This research shows how to make use of the competence of the experts to give their preferences to some features related to the kinds of mental disorder, it has not utilized Fuzzy Multiple Attribute Decision Making (FMADM) in the CGDSS application related to the uncertainty solution. The knowledge base is built based on the results of combining preferences through preference aggregation process using FMADM steps.

Then inference process is carried out to support diagnose the patients using Bayesian Belief Network (BBN).

There are several open problems in this research such as (1) developing of web based CGDSS system using the discussed model (2) accommodating preference acquisition methods for generating better knowledge from many experts (3) testing and validating, and utilizing the knowledge base having some preferences and the system performance.

References

- [1] Suiran, Y.U., and Kimura, F., "Evaluation Model of Design Alternatives Based on Multi-Criteria Decision Making", online on <http://www.cim.pe.u-tokyo.ac.jp/ic/publication-j.html>. 3rd June 2004.
- [2] Sage, A.P., 1991, *Decision Support Systems Engineering*. New York: John Wiley & Sons.
- [3] Klir, G.J., and Bo, Y., 1995, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. New York: Prentice Hall.
- [4] Terano, T., Asai, K., and Sugeno, M., 1992, *Fuzzy Systems Theory and Its Applications*. London: Academic Press.
- [5] Lee, H.-S., dan Lee, H.-C., 2003, "A Fuzzy Multiple Criteria Decision Making Model Based on Strength and Weakness Indices" online on 140.125.30.140/ai_conference2003/pdf/B053.pdf. 20th May 2005.
- [6] Herrera, F., and Herrera-Viedma, E., 2000, "Linguistic Decision Analysis: Steps for Solving Decision Problems Under linguistic Information" on *Elsevier: Fuzzy sets and Systems*, No. 115, Pp: 67-82.
- [7] Chu, T.-C., and Chang, T.-M., 2004, "Solving Fuzzy MCDM Using Fuzzy Weighted Average Arithmetic", online on <http://www.bus.sfu.ca/events/mcdm/MCDMProgram/Abstract1/AA10%20CF%20Chu%20taiwan%20Fuzzy%20MCDM.pdf> 12th April 2005.
- [8] Tsao, C.-T., 2004, "An Impact-Adjusted Fuzzy Multiple Criteria Decision Making", online on <http://www.bus.sfu.ca/events/mcdm/MCDMProgram/Abstract1/AA21%20CF%20tsao%20Fuzzy%20MCDM%20model.pdf>. 10th June 2005.
- [9] Chu, T.-C., 2002, "A Fuzzy Number Interval Arithmetic based Fuzzy MCDM Algorithm" on *International Journal of Fuzzy System*, Vol. 4, No. 4, Pp: 867-872. <http://www.im.stut.edu.tw/mrchu/> 12th March 2003.
- [10] Hon, C., Tang, L., and Peng, T., 2001, "Quantitative and Qualitative Analysis of Criteria Grading and Weight Setting in Performance Evaluation System Under Group Decision Making and Fuzzy Data" dalam *Proceedings of the 6th Annual International Conference on Industrial Engineering – Theory, Applications and Practice*. San Francisco. <http://www.cm.yzu.edu.tw/eng/Faculty/ltarn.g.htm>. 23th May 2005.
- [11] Ramnarayan, P., Kulkarni, G., Tomlinson, A., and Britto, J., "ISABEL: A Novel Internet-Delivered Clinical Decision Support System. Healthcare Computing" online on http://www.health-informatics.org/hc2004/P28_Ramnarayan. 12th November 2004.
- [12] Gardner, R.M., 2004, "Computerized Clinical Decision-Support in Respiratory Care", on *Respiratory Care*, Vol. 49, No. 4, Pp. 378-388, online on <http://www.rearden.cs.uiuc.edu/~qwang4/tmp/ComputerizedClinicalDecisionSupportInRespiratoryCare.pdf> . 05th August 2005.
- [13] Pichot, P., 1967, "La nosologie psychiatrique et le diagnostic par ordinateur", dalam *Presse Méd.*, No. 75, Pp: 1269-1274.
- [14] Spitzer, R. L., and Endicott, J., 1968, "DIAGNO: A computer program for psychiatric diagnosis utilizing the differential diagnostic procedure", on *Arch. Gen. Psychiatry*, No. 18, Pp: 746-756.
- [15] Heiser J.-F., and Brooks R. E., 1978, "Design considerations for a clinical psychopharmacology advisor", in *Proceedings., 2nd Ann. Symp. On Computer Applications in Medical Care* Pp: 278-285, New-York: IEEE.
- [16] Werner, G., 1987, "Methuselah—An expert system for diagnosis in geriatric psychiatry". *Computers and Biomed. Res.*, Vol. 20, No. 5, Pp: 477-478.
- [17] McWilliam, C., Forshaw, D., and Shiwach, R., 1988, "The geriatric mental state (GMS) used in the community: replication studies of the computerized diagnosis AGE-CAT".
- [18] Portelli, C., Frydman, F., and Mises, R., 1989, "Intelligence artificielle en pédo-psychiatrie: JPSY, un système expert d'aide au diagnostic".
- [19] Pluggue, L.A., Verhey, F.R.J., and Jolles, J., 1990, "A desktop expert system for the differential diagnosis of dementia : an evaluation study" on *International Journal of Technology Assessment in Health Care*, No. 6, Pp: 147-156.
- [20] Ohayon, M., and Poiso, Y., 1987, "Compatibilité du DSM-III avec la Nosographie Psychiatrique Française". *Psychologie Médicale*, Vol. 19, No. 3, Pp: 367-370".
- [21] Ma, J., Zhang, Q., Zhou, D., and Fan, Z.P., 2004, "A Multiple Person Multiple Attribute Decision Making Method Based on Preference Information and Decision Matrix", online on <http://www.is.cityu.edu.hk/Research/WorkingPapers/paper/0006.pdf>. 3th November 2004.
- [22] Zimmermann, 1991, *Fuzzy Set Theory an Its Applications*. 2nd Edition. Massachusetts: Kluwer Academic Publishers.
- [23] Murray, 2006, *Bayesian Belief Networks*, <http://www.murrayc.com/learning/AI/bbn.shtml>. November 2006.