

<http://ansinet.com/itj>

ITJ

ISSN 1812-5638

# INFORMATION TECHNOLOGY JOURNAL

**ANSI***net*

Asian Network for Scientific Information  
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

## Optimize of a Development Project Based on the VMD Method

Wang Hong-Xu

College of Science and Engineering, Qiongzhou University, China

**Abstract:** The VMD method is a method of vague pattern recognition. The detailed steps of this method are that: (1). Establish a scheme set. Need establish reserve scheme sets. Draw an optimal scheme set theoretically (2). Turn the original data turn into the vague data. Need that turn a monodrama data into a vague data and turn a language value data into a vague data and (3). Vague multiattribute decision. Fix the weight of the every index. Calculate weighing similarity measures between vague sets of the reserve scheme and vague set of an optimal scheme in theory. Vague multiattribute decision: By a maximal value of the weighing similarity measures a correspondence scheme is optimal scheme. Given a transforming formula from the monodromy value data to vague data. Presented a weighing similarity measure formula between vague sets. The application example of this method shows that this method and these formulas are useful.

**Key words:** Vague sets, transforming data, weighing similarity measures, the VMD method, application example

### INTRODUCTION

Gau and Buehrer (1993) present vague set theory and it is one of popularizes of fuzzy set theory (Zadeh, 1965). Owing to the fact that can clearly express affirm member degree and oppose member degree and not fix degree when using vague set theory describe fuzzy information, therefore vague set than fuzzy set have more advantages. In reference Yun *et al.* (2010) the Fuzzy-AHP-TOPSIS method and by use this method solve decision question of the optimization of multiattribute decision plan, and get a better application effect. Hope applies vague set theory and discusses an identical question in the essay.

### MEASURE SIMILARITY BETWEEN VAGUE SETS (VALUE)

**Definition 1: Hua-Wen and Hengyang (2004):** One of the data mining of a vague value is: Let vague value as  $h = [t_h, 1-f_h]$  and:

$$\begin{aligned} t_h^{(0)} &= t_h, f_h^{(0)} = f_h, \pi_h^{(0)} = \pi_h = 1 - t_h - f_h; \\ t_h^{(m)} &= t_h \cdot (1 + \pi_h + \pi_h^2 + \dots + \pi_h^m), \\ f_h^{(m)} &= f_h \cdot (1 + \pi_h + \pi_h^2 + \dots + \pi_h^m) \end{aligned}$$

$$\pi_h^{(m)} = \pi_h^{m+1}; p^{(m)}(h) = t_h^{(m)} - f_h^{(m)}, (m = 0, 1, 2, \dots).$$

**Definition 2: Wang (2010a):** Suppose vague values as  $h = [t_h - 1 - f_h]$ ,  $e = [t_e - 1 - f_e]$ , definition.

- Trivial axiom  $T(h, e) \in [0, 1]$
- Symmetric axiom  $T(h, e) = T(e, h)$
- Maximum axiom  $M(h, h) = 1$ ;
- Minimum axiom If the when  $h = [1, 1]$ ,  $e = [0, 0]$  or  $h = [1, 1]$ , there is  $M(p, e) = 0$ , or ever.

Then formula  $T(h, e)$  known as similarity measures between vague values  $h$  and  $e$ , if the  $T(h, e)$  content at the least mentioned axioms.

**Theorem 1:** Let vague values as  $h = [t_h, 1-f_h]$ ,  $e = [t_e, 1-f_e]$ , ( $m = 0, 1, 2, \dots$ ). Then:

$$T_m(h, e) = \left[ 1 - |t_h^{(m)} - t_e^{(m)}| \right] \cdot \left[ 1 - \frac{1}{2} |p^{(m)}(h) - p^{(m)}(e)| \right]$$

is the similarity measure between vague values  $h$  and  $e$ .

Copy definition 2 can be given to the definition of similarity measures between vague sets and to the definition of the weighted similarity measure between sets, no give a minute description. Theorem 2 will be described below with reference to the results.

**Theorem 2:** Suppose a universe of discourse is  $Z = \{z_1, z_2, \dots, z_n\}$ , on  $Z$  there is vague sets:

$$H = \sum_{i=1}^n [t_H(z_i), 1 - f_H(z_i)] / z_i$$

and

$$E = \sum_{i=1}^n [t_E(z_i), 1 - f_E(z_i)] / z_i$$

note simple as:

$$H = \sum_{i=1}^n [t_{h_i}, 1 - f_{h_i}] / z_i, E = \sum_{i=1}^n [t_{e_i}, f_{e_i}] / z_i$$

Then:

$$T_m(H, E) = \frac{1}{n} \sum_{i=1}^n \left[ 1 - |t_{h_i}^{(m)} - t_{e_i}^{(m)}| \cdot \left[ 1 - \frac{1}{2} |p_{h_i}^{(m)} - p_{e_i}^{(m)}| \right] \right] \quad (m=1, 2, \dots) \quad (1)$$

is the similarity measure between vague sets H and E.

**Theorem 3:** Let the elements of  $z_i$  the weight as the  $a_i \in [0, 1]$ :

$$\sum_{i=1}^n a_i = 1$$

in such as under the assumption of theorem 2. Then:

$$WT_m(H, E) = \sum_{i=1}^n a_i \cdot \left[ 1 - |t_{h_i}^{(m)} - t_{e_i}^{(m)}| \cdot \left[ 1 - \frac{1}{2} |p_{h_i}^{(m)} - p_{e_i}^{(m)}| \right] \right] \quad (m = 0, 1, 2, \dots) \quad (2)$$

is a weighted similarity measures between vague sets H and E.

### FROM THE ORIGINAL DATA TRANSFORM TO VAGUE DATA

In the study, an application example need a transforming formula from a monodromy data into the vague data. Such the transforming formulas are given by Wang (2010b). Below we get a so transforming formula.

**Definition 3: Wang (2010c):** Suppose a universe of discourse is  $Z = \{z_1, z_2, \dots, z_n\}$ , the data of index  $z_j$  ( $j = 1, 2, \dots, n$ ) of sets  $H_i$  ( $i = 1, \dots, m$ ) on  $Z$  are the monodromy data  $z_{ij}$  ( $\geq 0$ ). If a monodromy data  $z_{ij}$  ( $\geq 0$ ) transform to a vague data.

$H_i(z_j) = [t_{ij}, 1 - f_{ij}]$  satisfies vague axiom and returns axiom, then refer to this formula as returns type transforming formula. If satisfies vague axiom and consume axiom, then refer to this formula as consume type transforming formula. Here:

- Vague axiom:  $0 \leq t_{ij} \leq 1 - f_{ij} \leq 1$
- Returns axiom: If the  $z_{xj} > z_{yj} \geq 0$ ,  $z_{xj}$ ,  $z_{yj}$ , respectively, into the vague data as:

$$H_x(z_j) = z_{xj} = [t_{xj}, 1 - f_{xj}], H_y(z_j) = z_{yj} = [t_{yj}, 1 - f_{yj}]$$

- Content:  $t_{xj} \geq t_{yj}$ ,  $1 - f_{xj} \geq 1 - f_{yj}$ .
- Consume axiom: If the  $z_{xj} > z_{yj} \geq 0$ ,  $z_{xj}$ ,  $z_{yj}$ , respectively, into the vague data as:

$$H_x(z_j) = z_{xj} = [t_{xj}, 1 - f_{xj}], H_y(z_j) = z_{yj} = [t_{yj}, 1 - f_{yj}]$$

- Content  $t_{xj} \leq t_{yj}$ ,  $1 - f_{xj} \leq 1 - f_{yj}$ .

**Note:** When the index value takes the more bigger, the better, the appropriate make use of returns type transforming formula and when the index value takes "the more smaller, the more better, the appropriate make use of consume type transforming formula.

**Theorem 4:** Suppose:  $z_{jmax} = \max \{z_{1j}, z_{2j}, \dots, z_{mj}\}$ ,  $z_{jmin} = \min \{z_{1j}, z_{2j}, \dots, z_{mj}\}$  ( $j = 1, 2, \dots, n$ ). Then that:

$$H_i(z_j) = z_{ij} = \left[ \left( \frac{z_{ij} - z_{jmin}}{z_{jmax} - z_{jmin}} \right)^3, \left( \frac{z_{ij} - z_{jmin}}{z_{jmax} - z_{jmin}} \right)^{\frac{3}{2}} \right] \quad (3)$$

is a returns type transforming formula.

$$H_i(z_j) = z_{ij} = \left[ 1 - \left( \frac{z_{ij} - z_{jmin}}{z_{jmax} - z_{jmin}} \right)^{\frac{3}{2}}, 1 - \left( \frac{z_{ij} - z_{jmin}}{z_{jmax} - z_{jmin}} \right)^3 \right] \quad (4)$$

is a consume type transforming formula.

### THE VMD METHOD

Popularize Vague sets integrated decision-making rules that document (Yun *et al.*, 2010) gives, get the VMD (Vague multiattribute decision) method. The detailed steps of this method are that: (1). Establish a scheme set. Need establish reserve scheme sets. Draw an optimal scheme set theoretically: (2). Turn the original data turn into the vague data. Need that turn a monodromy data into a vague data and turn a language value data into a vague data. C. Vague multiattribute decision. Fix the weight of the every index and (3) calculate weighing similarity measures between vague sets of the reserve scheme and vague set of an optimal scheme theoretically. Vague multiattribute decision: By a maximal value of the weighing similarity measures a correspondence scheme is an optimal scheme.

**CASE**

By application vague multiattribute decision method restudy the example in reference (Yun *et al.*, 2010).

**Establish a scheme set:** Take up the indexes that  $z_1$  as: The recoverable reserves added value ( $10^8m^4$ ),  $z_2$  as: The unit a steel mean (Mpa/km),  $z_3$  as: Total power required to the compressor (kw),  $z_4$  as: The scheme investment,  $z_5$ : Financial internal rate of return (%),  $z_6$ : Financial net present value rate (%),  $z_7$ : Technological risks,  $z_8$ : Management risk. They constitute an index set. Take up the schemes that  $H_1$  as: Scheme 1,  $H_2$  as: Scheme 2,  $H_3$ : as: Scheme 3,  $H_4$ : as: Scheme They constitute a scheme set.

Because the indexes  $z_1$ ,  $z_2$  and  $z_6$  are and the more and bigger, the better. And the other indexes are and the more and smaller, the better. Therefore, get a must optimize scheme on the theory E (Table 1).

**From the primary data change to vague data:** In the Table 1 indexes  $z_7$  and  $z_8$  are the primary data expressed by the nature language of the people, by the expert may direct give corresponding vague data as: very low [0.00, 0.15], low [0.15, 0.29], lower [0.29, 0.43], general [0.43, 0.57], higher [0.57, 0.71], high [0.71, 0.85], very high [85,100].

Indexes  $z_1$  and  $z_5$  and  $z_6$ , are the and the more and bigger, the better. Application formula (3) calculate indexes  $z_1$  and  $z_5$  and  $z_6$ . And other indexes are and the more and smaller, the better. Application formula (4) calculate other indexes Table 2.

By Table 2, already get that the vague sets of the schemes  $H_1$ ,  $H_2$ ,  $H_3$ ,  $H_4$  and a vague set of an most optimize scheme on the theory E.

**Vague multiattribute decision:** Note the weighs of the elements of reference (Yun *et al.*, 2010) for the  $a_1 = 0.3313$ ,  $a_2 = 0.1059$ ,  $a_3 = 0.0327$ ,  $a_4 = 0.1572$ ,  $a_5 = 0.2307$ ,  $a_6 = 0.0709$ ,  $a_7 = 0.0477$ ,  $a_8 = 0.0236$ . And take  $m = 2$ , Application formula (2) calculate the weighted similarity measures between vague sets  $H_i$  ( $m = 0,1,2, \dots$ ) and E. The results are follows:

$$WT_2(H_1,E) = 0.53, WT_2(H_2,E) = 0.36, \\ WT_2(H_3,E) = 0.50, WT_2(H_4,E) = 0.49$$

According as the big or small of the weighted similarity measure values can be getting following order of the schemes: scheme  $H_1$ , scheme  $H_3$ , scheme  $H_4$ , scheme  $H_2$ . An optimal scheme is scheme  $H_1$ .

Table 1: Indexes data of scheme influence factors (original)

Sch. $H_i$	$H_1$	$H_2$	$H_3$	$H_4$	E
$z_1$	0.61	0.61	0.91	0.91	0.91
$z_2$	0.044	0.035	0.039	0.036	0.035
$z_3$	439	313	580	512	313
$z_4$	1430	1718	2238	2317	1430
$z_5$	25.7	20.1	23.4	22.4	25.7
$z_6$	57.1	33.3	47.4	42.8	57.1

Table 2: Indexes data of scheme influence factors (vague)

Sch. $H_i$	$H_1$	$H_2$	$H_3$	$H_4$	E
$z_1$	[0.00,0.00]	[0.00,0.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]
$z_2$	[1.00,1.00]	[0.00,0.00]	[0.09,0.30]	[0.00,0.00]	[1.00,1.00]
$z_3$	[0.10,0.32]	[0.00,0.00]	[1.00,1.00]	[0.42,0.65]	[1.00,1.00]
$z_4$	[0.00,0.00]	[0.03,0.17]	[0.75,0.87]	[1.00,1.00]	[1.00,1.00]
$z_5$	[1.00,1.00]	[0.00,0.00]	[0.21,0.46]	[0.07,0.26]	[1.00,1.00]
$z_6$	[1.00,1.00]	[0.00,0.00]	[0.21,0.46]	[0.06,0.24]	[1.00,1.00]
$z_7$	[0.15,0.29]	[0.00,0.15]	[0.57,0.71]	[0.43,0.57]	[0.00,0.15]
$z_8$	[0.29,0.43]	[0.15,0.29]	[0.71,0.85]	[0.71,0.85]	[0.15,0.29]

**CONCLUSION**

Yun *et al.* (2010) applied Fuzzy-AHP-TOPSIS method studied the problem; need to used fuzzy matrix calculation, this method approaches can theoretically guarantee the optimum, but it costs long time and request large EMS memory. The VMD method is one of the vague patted recognition methods. A tool of the patted recognition is a similarity measure formula and a weighing similarity measure formula between vague sets. The application example shows that this method is convenient and simple. The result is eff.

**REFERENCES**

Gau, W.L. and D.J. Buehrer, 1993. Vague sets. IEEE. Syst. Man Cybernet., 23: 610-614.  
 Hua-Wen, L. and W. Hengyang, 2004. Transformations and similarity measures of vague sets. Comput. Eng. Appl., 40: 79-81, 84.  
 Wang, H.X., 2010a. Definition and transforming formulas from single valued data to vague valued data. Comput. Eng. Appl., 46: 42-44.  
 Wang, H.X., 2010b. Formula for similarity measures between vague sets and its application. Comput. Eng. Appl., 46: 198-199.  
 Wang, H.X., 2010c. Synthesis decision rule of vague sets and its application in scheme optimum. Comput. Eng. Appl., 46: 145-147.  
 Yun, C., C. Quan and S. Shao-Quan, 2010. The application of fuzzy-ahp-topsis in multi-attribute. Math. Practice Theory, 40: 86-91.  
 Zadeh, L.A., 1965. Fuzzy sets. Inform. Control, 8: 338-353.