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Efficiency Evaluation on Time Management with Fuzzy Data

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ABSTRACT

People's performance on time management is highly embedded in the issue of management science. In this paper, we use soft computing techniques and fuzzy statistical tools to evaluate people's performance on time management. Through a standardized measurement system, we generate real value data to satisfy not our current needs, but those of the data themselves. This is when fuzzy classification stands out and highlights the gray area of in-between and undefined. The proposed metric system helps us to assess the distance among trapezoidal fuzzy data. The index of efficiency between observed time and ideal time is also presented. With the ranking of the fuzzy sample, we can examine the decision process using a nonparametric testing hypothesis. Methodologically, the paper constitutes a pre-project test of a new formula for treating fuzzy data in interval, triangular, and trapezoidal form.

1. Introduction

One cannot talk about promoting the quality of enterprise management without tackling the problem of implementing an efficiency evaluation tool, such that we will be able to systematically gauge and monitor our work performance. But how can we apply a measurable system? The answer is that we will need to set up a metric system for sampling survey or field studies. A great deal of effort [1–7] has been devoted to ranking a set of fuzzy numbers. For instance, Liu, Wu, and Liu (2008) provide a new ranking procedure that is consistent with preferences of the conservative investors. Their ranking procedure satisfies the axioms of three order relations for separable fuzzy numbers. Ramli and Mohamad (2009) conducted a comparative analysis of centroid methods in ranking fuzzy numbers. Kumar et al (2010) proposes an RM approach for ranking generalized trapezoidal fuzzy numbers. However, most methods are not designed to consider evaluation problems. This implies that the fuzzy numbers ranked by these methods are not consistent with the actual preferences of the managers.

Murphy (1990) finds that school leaders spend most of their time in curriculum and instruction, while spending less on student' discipline, parent relations, school facilities and school financial management. Samuels (2008) claims that most leaders hope that, at least half their working day may be spent on meaningful interactions with teachers and students, but that is not likely. Leaders spend only a third, or less, of their day, in this way. Often, the contact with teachers and students is too short and unfocused to lead to actual instructional improvement. In the present research, we shall investigate the

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effectiveness of leaders' management and efficiency of time allocation through the application of fuzzy set theory.

Furthermore, in many fields (such as human language, thought and decision making), where categorization (or ranking) is vague, non-quantitative, or even non-specific to preferences, significant data may easily slip through our fingers. Most extant literature have fail to consider soft computing with the statistics of actual and expected time for people's business hours. Until now, few researchers use fuzzy statistics and operations to compute trapezoidal data. Since human thinking is subjective and complex, a fuzzy approach allows research on statistical analysis to be more precise, permitting researchers to further analyze the data. The use of soft statistical methods becomes more data transparent.

Since statistical phenomena can easily and quickly describe the basic structure of the information for data analysis, they have been widely employed in many academic areas. The mean is the most popular among them. However, when we wish to understand the research target's opinions or consensus on some public issues, the application of the mode will be more proper than mean. But since the mode for traditional statistics only involves a single number and is unable to express the human thought and the complexity of subjective matter, the fuzzy mode should be developed to yield greater fidelity and detailed description for these issues. Fuzzy theory describes the membership between [0, 1] to illustrate the relationship between elements and sets.

2. Statistical Analysis with Fuzzy Data

2.1 Fuzzy Questionnaire

The question we will need to ask is what statistical tools should be included in the evaluation. Since evaluation needs to be aligned with the same logical base, there should also be significant differences on the metrics being used. The key in this effort is to find the well established evaluation system that is consistent with our own goals and objectives.

Following the research of FGRS (Fuzzy Graphic Rating Scale) presented by Hesketh, Pryor, Gleitzman, & Hesketh (1988); Costas, Maranon, & Cabrera (1994) chose 100 university students as a study sample and found that FGRS fits the features of human psychology.

Herrera, Herrera-Viedma, & Martinez (2000) presented the steps of linguistic decision analysis under linguistic information. Their statements believed that there are certain degrees of possibilities to express linguistics based on fuzzy number, but it should be reconsidered that if the response will produce the same fuzzy number.

Liu & Song (2001) developed one type of measurement whose linguistic is similar with semantic proximity. Based on the similarity of linguistic concept, they present a formula of fuzzy association degree. Liu & Song (2001) use the information of botany as an example to illustrate and analyze the categorical similarity of rare plant in the ecology. Carlsson & Fuller (2000a), Carlsson & Fuller (2000b), Chiang, Chow, & Wang (2000), Herrera, Herrera-Viedma, & Martinez (2000), Dubois & Prade (1991) have discussed many concepts about the computation of fuzzy linguistic and these concepts are worthy to popularized.

Based on these archives from previous research, we may make two inferences:

(i) The methods of traditional statistical analysis and measurement used in public consensus are incomplete and inadequate. Based on the real fuzzy features of human thought, quantifying the measurement of public consensus processed by fuzzy numbers should be seriously considered and discussed.

(ii) The measurement of attitudes and feelings based on fuzzy set theory has emerged as a very critical method in recent years. There are many associated scholarly fields in this type of research.

Even though, educational and psychological applications are still limited. In conclusion, the theoretical research on the fuzzy mode and the experimental discussion presented in this paper may serve as a possible solution with significant potential.

2.2 Statistical analysis with fuzzy data

In social science research, the sample survey is frequently used to evaluate and understand public opinion on certain issues. The traditional survey forces people to choose one fixed answer from the survey, but ignores the uncertainty of human thinking. People are required to choose one answer from the survey which lists five choices including "Very satisfactory," "Satisfactory," "Normal," "Unsatisfactory," "Very unsatisfactory," when in fact that the answer to the question is most likely continuous. This limits the flexibility of the answer and forces people to choose fixed answers. For instance, when the survey proposes to ascertain the answer for sleeping hours of a person, it will be difficult to describe the feeling or understanding reasonably unless fuzzy statistics are adopted.

Since traditional statistics deals with a single answer or a certain range of the answer through sample survey, it is unable to sufficiently reflect the thought of an individual. If, on the other hand, respondents can use the membership function to express the degree of their feelings based on their own choices, the answer presented will be closer to real human thinking. Therefore, to collect the information based on the fuzzy mode should be more reasonable. In consideration for questions related to the fuzzy property, the information itself has uncertainty and fuzzy properties. The following are the definitions of the discrete fuzzy mode and the continuous fuzzy number. The discrete fuzzy mode is simpler than the continuous fuzzy mode. The computation of the discrete number is easier than the continuous one.

Since many sample surveys are closely related with fuzzy thinking when the factors of set can be clearly grouped into many categories, it will be useful if we apply discrete fuzzy numbers in the public consensus.

Continuous fuzzy data can be classified into several types, such as interval-valued numbers, triangular numbers, trapezoidal numbers, exponential numbers, etc. Most fuzzy numbers get these names from the shape of the membership function. Even though there are various types of fuzzy numbers, we limit the discussion here to three usual types: interval-valued numbers, triangular numbers and trapezoidal numbers. The definitions of the three types of fuzzy data are given as follows.

Definition 2.1 *A fuzzy number* $A=[a,b,c,d]$, *defined on the universe set U of real number R with its vertex* $a \le b \le c \le d$, *is said to be a trapezoidal fuzzy number if its membership function is given by*

$$u_A(x)=\begin{cases} \dfrac{x-a}{b-a} \quad , & a \le x \le b \\ 1 \quad , & b \le x \le c \\ \dfrac{d-x}{d-c} \quad , & c \le x \le d \\ 0 \quad , & \text{otherwise} \end{cases}$$

when $b=c$, A *is called a triangular fuzzy number; when* $a=b$ *and* $c=d$, A *is called an interval-valued fuzzy number.*

Definition 2.2 *Fuzzy expected values*

Let $A_i=[a_i,b_i,c_i,d_i]$ *be a sequence of random trapezoid fuzzy sample on* U . *Then the fuzzy expected value is defined as* $E(X)=[\frac{1}{n}\sum_{i=1}^{n}a_i,\frac{1}{n}\sum_{i=1}^{n}b_i,\frac{1}{n}\sum_{i=1}^{n}c_i,\frac{1}{n}\sum_{i=1}^{n}d_i]$.

Definition 2.4 *Fuzzy expected values (data with multiple values)*

Let $L=\{L_1,L_2,\cdots,L_k\}$ *be a set of k-linguistic variables on* U , *and*

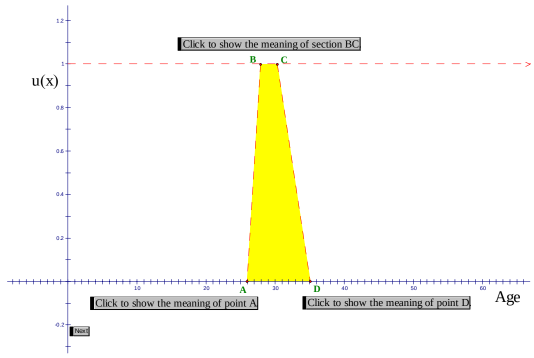
$\{FS_i = \frac{m_{i1}}{L_1} + \frac{m_{i2}}{L_2} + ... + \frac{m_{ik}}{L_k}, i = 1,2,...,n\}$ *be a sequence of random fuzzy sample on* U, $m_{ij}(\sum_{j=1}^{k} m_{ij} = 1)$ *is the memberships with respect to* L_j. *Then, the Fuzzy expected value is defined as* $E(X) = \frac{\frac{\sum_{i=1}^{n} m_{i1}}{n}}{L_1} + \frac{\frac{\sum_{i=1}^{n} m_{i2}}{n}}{L_2} + ... + \frac{\frac{\sum_{i=1}^{n} m_{ik}}{n}}{L_k}$.

2.3 Getting a continuous fuzzy data

Respondents choose one single answer or a certain range of the answer in the traditional sample survey. But the traditional method is not able to truly reflect the complex thoughts of each respondent. If people can express the degree of their feelings by using membership functions, the answer presented will be closer to real human thoughts. Unfortunately, scholars disagree in their opinion about the construction of continuous fuzzy data. Many studies use continuous fuzzy constructs without describing the construction method. The core of all the questions is fuzzy data determined by a membership function, but the construction of the membership function is quite subjective. To reflect this, we ask the respondents to determine the membership function based on GSP.

Figure 2.1 presents the image of a fuzzy questionnaire on the prime time for marriage. Before answering the fuzzy questionnaire, respondents could click the three buttons to realize the meaning of each section and points. For example, people may decide: $\overline{AB}$ which represents the desire for marriage grows continuously for 20 years from 26. $\overline{BC}$ represents the desire for optimal marriage is 28~30. $\overline{CD}$ represents the desire for marriage falls continuously from 30 until it reaches 35.

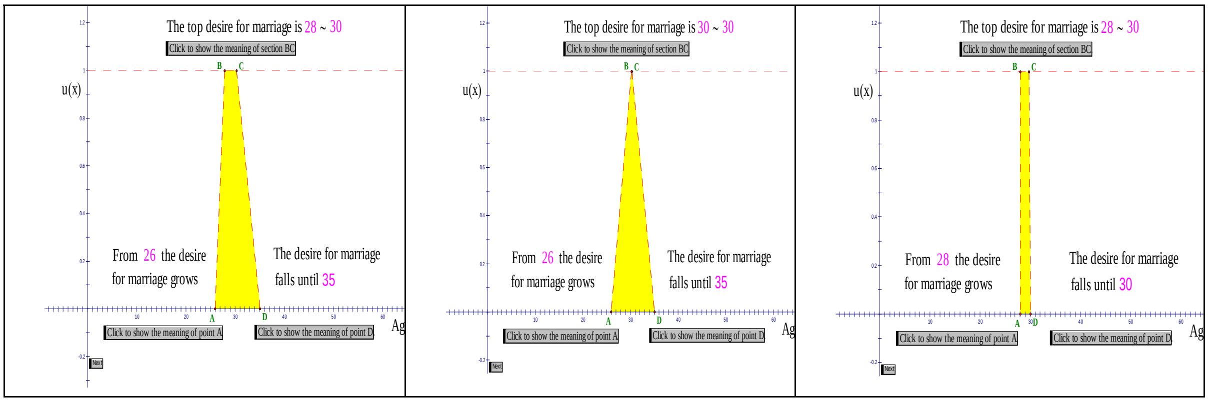
Figure 2.1 a fuzzy answer for the expected marriage age



Respondents can decide their own membership function of the prime time for marriage by moving the four points *A*, *B*, *C*, and *D*. By moving the four points, the age corresponding to the points will be change automatically. Fig. 9 is a special case of trapezoid when point *B* equals to point *C*. It represents the prime time for marriage is only 30. Fig. 10 shows the prime time for marriage is 28~30.

There are probably three types of fuzzy data: The first is trapezoidal; the second is triangular; the third is interval-valued type. Figure 2.2 illustrates these three kinds of fuzzy data.

Figure 2.2 Fuzzy observation for idea marriage year



3. Measurement computation and ordering with fuzzy data

3.1 Ordering the fuzzy data

A trapezoidal fuzzy set can be viewed as a continuous fuzzy set, which further represents uncertain events. When a sample of trapezoidal data is presented, we are interesting in scaling its value on the real line. In some practical applications, however, it is reasonable to consider, instead of the original class of all linear re-scalings, a more general class of non-linear transformations between scales. For example, the energy of an earthquake can be described both in the usual energy units and in the logarithmic (Richter) scale. Similarly, the power of a signal can be measured in watts, but it can also be measured in the logarithmic scale of decibels.

When we consider the reasonable and meaningful conditions to map trapezoidal data onto the real line, we need to identify two conditions. This means that the data to be transformed should be finite-dimensional and the dependence on these parameters should be smooth (differentiable). In mathematical terms, this means that our transformation group is a Lie group.

Once such a transformation is selected, instead of the original trapezoidal data, we have a new value y = f(x). In the ideal situation, this new quantity y is normally distributed. (In practice, a normal distribution for y may be a good first approximation.) When selecting the transformation, we must take into account that, due to the possibility of rescaling, the numerical values of the quantity x are not uniquely determined.

Definition 3.1 ***Scaling for a trapezoid fuzzy number on R***

Let $A=[a,b,c,d]$ *be a trapezoid fuzzy number on U with its centroid*

$$(cx,cy)=\left(\frac{\int x u_A(x)dx}{\int u_A(x)dx},\ \frac{\int \frac{1}{2}(u_A(x))^2 dx}{\int u_A(x)dx}\right).$$

Then the defuzzification number RA of $A=[a,b,c,d]$ *is defined as*

$$RA = cx + \left(1-\frac{\ln(1+\|A\|)}{\|A\|}\right);$$

where, $\|A\|$ *is the area of the trapezoid.*

Note that for convenience we will write $RA=\dfrac{-(a+b)^2+(c+d)^2+(ab-cd)}{3((c+d)-(a+b))}$, if A is a trapezoid; $RA=\dfrac{a+b+d}{3}$, if A is a triangle; $R(A)=\dfrac{b+c}{2}$, if A is an interval.

Example 3.1 *Let* $A_1=[2,2,3,3]$, $A_2=[1,1,4,4]$, $A_3=[1,2.5,2.5,4]$,

$A_4 = [1,2.5,2.5,8]$, $A_5 = [1,2,3,4]$, $A_6 = [1,2,3,8]$

Then,

$RA_1 = 2.5 + (1 - \frac{\ln(1+1)}{1})$ =2.5+0.3069=2.8069,

$RA_2 = 2.5 + (1 - \frac{\ln(1+3)}{3})$ =2.5+0.5379=3.0379

$RA_3 = 2.5 + (1 - \frac{\ln(1+1.5)}{1.5})$ =2.5+0.3891=2.8891,

$RA_4 = 3.83 + (1 - \frac{\ln(1+3.5)}{3.5})$ =3.83+0.5703=4.3

$RA_5 = 2.5 + (1 - \frac{\ln(1+2)}{2})$ =2.5+0.4507=2.9507,

$RA_6 = 3.79 + (1 - \frac{\ln(1+4)}{4})$ =3.79+0.5976=4.3876.

3.2 Distance among fuzzy data

However, there is little extant literature or definition of the measurement system. In this section, we will propose a well-defined distance for trapezoidal data.

Definition 3.2 *Let* $A_i = [a_i, b_i, c_i, d_i]$ *be a sequence of trapezoidal fuzzy number on U with its centroid*

$$(cx, cy) = \left(\frac{\int x u_A(x)dx}{\int u_A(x)dx}, \frac{\int \frac{1}{2}(u_A(x))^2 dx}{\int u_A(x)dx}\right).$$

Then the distance between the trapezoid fuzzy number A_i *and* A_j *is defined as*

$$d(A_i, A_j) = |cx_i - cx_j| + \left| \frac{\ln(1+\|A_i\|)}{\|A_i\|} - \frac{\ln(1+\|A_j\|)}{\|A_j\|} \right|$$

Example 3.2 *Let the fuzzy data be* $A_1 = [2,2,3,3]$, $A_2 = [1,1,4,4]$, $A_3 = [1,2.5,2.5,4]$, $A_4 = [1,2.5,2.5,8]$, $A_5 = [1,2,3,4]$, $A_6 = [1,2,3,8]$. *Then*

$d(A_i, A_j)$	$A_1 = [2,2,3,3]$	$A_2 = [1,1,4,4]$	$A_3 = [1,2.5,2.5,4]$	$A_4 = [1,2.5,2.5,8]$	$A_5 = [1,2,3,4]$	$A_6 = [1,2,3,8]$
$A_1 = [2,2,3,3]$	*0*	*0.2310*	*0.0823*	*1.3862*	*0.1438*	*1.5808*
$A_2 = [1,1,4,4]$		*0*	*0.1488*	*1.3574*	*0.0872*	*1.3497*
$A_3 = [1,2.5,2.5,4]$			*0*	*1.5111*	*0.0616*	*1.4985*
$A_4 = [1,2.5,2.5,8]$				*0*	*1.4769*	*0.0674*
$A_5 = [1,2,3,4]$					*0*	*1.4369*
$A_6 = [1,2,3,8]$						*0*

The distance states the gap between observed data and expected value; the smaller the distance the better the fit of the observed data with the expected values.

In order to generate a clear picture about the distance between ideal and actual data we need the following definition about efficiency, for which the value will be a standardized constraint on 0 and 1. We use exponential transformation f(x) to transform the distance of fuzzy data set of possible values of *x* into (0,1). A natural symmetry requirement explains the selection of an exponential function as an appropriate transformation of all positive quantities.

Definition 3.3 *Index of efficiency (IE) between idea and actual even*

Let U be the universe of discourse. Let $O = [a_o, b_o, c_o, d_o]$ *be the observed fuzzy sample and* $E = [a_e, b_e, c_e, d_e]$ *be the expected value from U. the index of efficiency between observed and idea data is defined as*

$$IOE = e^{-\left(\frac{|c_o - c_e|}{\ln(1+|c_e|)} + \left|\frac{\ln(1+\|O\|)}{\|O\|} - \frac{\ln(1+\|E\|)}{\|E\|}\right|\right)};$$

Where c_o and c_e stand for the centroid on x-axis of the observed and expected value.

A higher value of *IOE* indicates more efficient time management. If *IE*= 1, we say the event is absolutely efficient in its time management. If *IE*=0, we say the event is not efficient at all.

4. Empirical studies

4.1 Efficiency of time administration for managers

In the sampling survey about efficient time management during May and June 2010, we ask for 40 mangers from the median sized company from Taipei city to reply the questionnaires: Ages from 30 to 60, male 29 and female 11[1]. From the result of the sampling survey, we find that they spend 26~38 hours a week at the management work. This includes: 20~25 hour for the office hours, 2-5 hours for extended work after, 2~4 hours for leisure time and 2~4 hours for standby. Table 4.1 demonstrates a statistical result for this field studies.

Using definition 3.4 and 3.5 in section 3.4, we can compute the gap between actual and expected working time. Table 4.2 illustrates the distance and indices of efficiency for three types of time allocation.

From Table 4.2 we can see the distance between observed and expected time. The IOE of innovative/development reaches a maximum of 0.82, administration 0.46 is second, and public relation is last with 0.19. From this investigation, we can draw the conclusion that the managers' innovative/development skill is closest to ideal. It also demonstrates that the level is highly efficient. But the data display greater individual differences and thus polarization. The time spent on public relations leadership is lowest and the biggest gap indicates the poor performance.

[1] The sampling survey collected from a short survey (face to face) during 2010 summer (May - June). The place was the center of Taiwan (Taichung city). Data were collected by the author's Ph.d students. The 40 managers were chosen from Taichung city . No specific kind of enterprise or company was targeted.

4.2 Wilcoxon signed-ranks test with fuzzy data

As mentioned, the sign test with fuzzy data utilizes only the sign of the difference between $R(A_i)$ and $R(M_0)$. There exits another procedure with fuzzy data called the Wilcoxon signed-ranks test, under which the magnitude of the differences are concerned. Because the Wilcoxon signed-ranks test uses more data information than the sign test, it is often more powerful.

Assumption: Each of two fuzzy observations has *n* subjects. Let *i* denote the particular subject that is being referred to, the first fuzzy observation measured on subject i by A_i and the second fuzzy observation by B_i.

Hypotheses (under the significant level α.)

A. $H_0: M = M_0$ *vs* $H_1: M \neq M_0$

B. $H_0: M \geq M_0$ *vs* $H_1: M < M_0$

C. $H_0: M \leq M_0$ *vs* $H_1: M > M_0$

Testing statistic

The Wlicoxon signed rank statistic W^+ is computed by ordering defuzzification data RA_i, RB_i from smallest to largest. The rank of fuzzy sample A_i, B_i is given a rank of r_i. In this situation, we assign each tied value the mean of the rank positions. For example, if the three smallest entries are all equal, rank them 1, 2, and 3, but assign each a rank of $\frac{1+2+3}{3} = 2$.

Table 4.1 A comparison among different response about the importance of management

	defuzzy score	*membership*	*actual(hours/week)*
administration	*1.4*	*42.3%*	*(21.0, 31.6)*
innovative /development	*1.8*	*38.1%*	*(15.7, 23.2)*
public relations	*2.8*	*20.1%*	*(4.9, 8.2)*

Table 4.2 The distances and indies for the three types of management

	Actual	*Expected*	$d(O,E)=\lvert c_o-c_e\rvert+\left\lvert\frac{ln(1+\lVert O\rVert)}{\lVert O\rVert}-\frac{ln(1+\lVert E\rVert)}{\lVert E\rVert}\right\rvert$	*Efficiency Indies (IOE)=* $e^{-(\frac{\lvert c_o-c_e\rvert}{ln(1+\lvert c_e\rvert)}+\left\lvert\frac{ln(1+\lVert O\rVert)}{\lVert O\rVert}-\frac{ln(1+\lVert E\rVert)}{\lVert E\rVert}\right\rvert)}$
Adinistration	[21, 29]	[19, 22]	*4.69*	$e^{-1.65}=0.19$
Innovative /development	[15, 20]	[16, 20]	*0.54*	$e^{-0.2}=0.82$
Public relations	[5, 8]	[7, 9]	*1.59*	$e^{-0.77}=0.46$

Denote

$$I_i^+=\begin{cases}1,\ RB_i>RA_i>0\\0,\ otherwise\end{cases},\quad I_i^-=\begin{cases}1,\ RB_i<RA_i\\0,\ otherwise\end{cases}.$$

The Wilcoxon signed ranked statistic W^+ is defined as $W^+=\sum_{i=1}^n I_i^+r_i$, while W^- is defined as $W^-=\sum_{i=1}^n I_i^-r_i$. To simplify notation, we call the smaller of the two *T*, i.e. $T=\min\{W^+,W^-\}$.

Decision rules *for each set of hypotheses listed above are as follows.*

A. Reject H_0 *at a* α *level significance if* $T\le W_{\frac{\alpha}{2}}$.

B. Reject H_0 *at a* α *level significance if* $W^+\le W_{\frac{\alpha}{2}}$.

C. Reject H_0 *at a* α *level significance if* $W^-\le W_{\frac{\alpha}{2}}$.

A survey showed that wives spend more time per week on housework than do husbands. In order to check this finding, eleven couples were invited to complete a fuzzy questionnaire on the time spent on housework per week. The calculations for obtaining the test statistics are summarized in Table 4.3.

Table 4.3 Housework time

Couple	Husband (A_i)	Wife (B_i)	$R(A_i)$	$R(B_i)$	RA_i-RB_i	sign	r_i
1	[0,1,2]	[5,6.5,8]	1.31	6.89	-5.58	-	10
2	[5,6,7]	[6,7,10,11]	6.31	9.10	-2.79	-	5
3	[1,2,3]	[4,5,7]	2.31	5.89	-3.58	-	8
4	[4,6,7]	[6,7,10,11]	6.39	9.10	-2.71	-	6
5	[4,6]	[5,7]	5.45	6.45	-1.00	-	2
6	[6,7,9]	[8,9,10]	7.89	9.31	-1.56	-	3
7	[3.5,4,5,5.5]	[6,7,9]	4.81	7.89	-3.00	-	7
8	[6,7,9,9]	[4,6,7]	8.00	5.89	2.11	+	4
9	[5,6,7,8]	[6,7,8]	7.00	7.31	-0.36	-	1
10	[7,9,11]	[3,5,6]	9.54	4.89	4.65	+	9
11	[0,2]	[6,8]	1.45	7.45	-6.00	-	11

$W^+=\sum_{i=1}^{11}I_i^+r_i=13$, $W^-=\sum_{i=1}^{11}I_i^-r_i=53$, N=11.

M *= the median of the time which females spend on housework per week.*
M_0 *= the median of the time which males spend on housework per week.*

$H_0: M=M_0\ \ vs\ \ M>M_0$.

Under the $\alpha = 0.05$ level of significance, since $W^+ = 13 < W_{0.05} = 14$, we reject H_0. That is: wives spend more time on housework than husband do.

5. Conclusions

Soft computing techniques are growing in popularity as a new discipline from the necessity of dealing with vague samples and imprecise information caused by human complex thought in certain experimental environments. In this paper, we have made an attempt to budget the gap between the binary logic-based multiple choice survey and the more complicated yet precise fuzzy membership function assessment.

We have carefully demonstrated how to use fuzzy statistics in people's time management effectiveness of fuzzy time allocation and management assessments. The proposed IOE is a useful measure to evaluate the efficiency of people's time management. Empirical studies demonstrate how to measure fuzzy data that can deal with trapezoid, triangular, and interval-valued data simultaneously and to performing the nonparametric testing hypothesis.

The panorama proposed above can supply us with more sophisticated and detailed interpretations of our data than the conventional ones, especially when our data could not exhibit clear cut human thought. Moreover, it triggers the question for constructing continuous fuzzy data which truthfully explains the flow of human ideology.

Finally three points are suggested for future investigation:

1. In order not to spend inordinate time in inappropriate implementation, it is an urgent project to provide people with a time management training course to assist them to work efficiently.
2. We can further our research on data simulation to better understand features of the fuzzy linguistic, multi-facet assessment, and the balance of the moving consensus. Moreover, the choice of different α-cuts will influence the statistical results. An appropriate criterion for selecting significant α-cuts should be investigated in order to reach the best consensus among human beings.
3. There are other types of membership functions we could explore in the future. For the fuzzy mode of the continuous type, we can extend the uniform and triangular types of membership functions to non-symmetric or multiple peak types.

References

Carlsson, C. and Fuller, R., 2000a, Benchmarking in linguistic importance weighted aggregations. Fuzzy Sets and Systems 114, 35-41.

Carlsson, C. and Fuller, R., 2000b, Multiobjective linguistic optimization. Fuzzy Sets and Systems 115, 5-10.

Chiang, D. A., Chow, L. R. and Wang, Y. F., 2000, Mining time series data by a fuzzy linguistic summary system. Fuzzy Sets and Systems 112, 419-432.

Chu, T. and Tsao, C., 2002, Ranking fuzzy numbers with an area between the centroid point and original point. Comput. Math. Appl. 43, 111–117.

Costas, C. S. L., Maranon, P. P. and Cabrera, J. A. H., 1994, Application of diffuse measurement to the evaluation of psychological structures. Quality and Quanty 28, 305-313.

Dubois, D. and Prade, H., 1991, Fuzzy Sets in Approximate Reasoning, Part 1: Inference with Possibility Distributions. Fuzzy Sets and Systems 40, 143-202.

Herrera, F. and Herrera-Viedma, E., 2000, Linguistic decision analysis: steps for solving decision problems under linguistic information. Fuzzy Sets and Systems 116, 67-82.

Hesketh, B., Pryor, R., Gleitzman, M. and Hesketh, T., 1988, Practical applications and psychometric evaluation of a computerized fuzzy graphic ration scale. In T. Zetenyi(ed.) Fuzzy Sets in Psychology, 425-454, North-Holland, New York.

Kumar, A., Singh, P., Kaur, A. and Kaur, P., 2010, RM approach for ranking of generalized trapezoidal fuzzy numbers. Fuzzy Information and Engineering 2 (1), 37-47.

Liu, H., Wu, B. and Liu, M., 2008, Investors' preference order of fuzzy numbers. Computers and Mathematics with Applications. 55, 2623-2630.

Liu, W. Y. and Song, N., 2001, The fuzzy association degree in semantic data models. Fuzzy Sets and Systems 117, 203-208.

Liu, X. and Han, S., 2005, Ranking fuzzy numbers with preference weighting function expectations. Comput. Math. Appl. 49.

Murphy, J., 1992, The landscape of leadership preparation: Reframing the education of school administrators. Newbury Park, CA: Corwin Press, Inc.

Nguyen, H. and Wu, B., 2006, Random and fuzzy sets in coarse data analysis. Computational Statistics and Data Analysis 51, 70-85.

Ramli, N. and Mohamad, D., 2009, A Comparative Analysis of Centroid Methods in Ranking Fuzzy Numbers. European Journal of Scientific Research 28(3),492-501.

Samuels, C. A., 2008, Managers help leaders balance time. Education Week 27(23), 18-19.

Spillane, J. P., Eric, M. C. and Amber S. P., 2007, Taking a distributed perspective to the school leader's workday. Leadership and Policy in Schools 6(1), 103–125.

Yong, D., Zhu, Z. and Liu, Q., 2006, Ranking fuzzy numbers with an area method using radius of gyration. Comput. Math. 51, 1127–1136.

Yu, S. and Wu, B., 2009, Fuzzy item response model: a new approach to generate membership function for psychological measurement. Quality and Quantity 43(3), 381-390.

Zedah, L. A., 1999, Fuzzy sets. Information and Control 8, 338-353.