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Berlin Wu, Hung T. Nguyen,

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Berlin Wu
Department of Mathematical Sciences, National Chengchi University, Taipei, Taiwan, and
Hung T. Nguyen
Department of Mathematical Sciences, New Mexico State University, Las Cruces, New Mexico, USA

Abstract

Purpose – The purpose of this paper is to use soft computing technique and fuzzy statistical tool to evaluate people's performance on the marketing research and time management.

Design/methodology/approach – Through standardized measurement system, the authors come up with real-value data to satisfy not the current needs but data itself. This is when fuzzy classification stands out and highlights the area of in-between and undefined.

Findings – The proposed metric system helps the authors to assess the distance among trapezoidal fuzzy data. The index of efficiency between observed time and ideal time is also presented.

Originality/value – With the ranking of fuzzy sample, the authors can examine the decision process by non-parametric testing hypothesis.

Keywords Fuzzy sets, Efficiency evaluation, Time management, Index of efficiency

Paper type Research paper

1. Introduction

One cannot talk about promoting the quality of enterprise without tackling the problem of implementing an efficiency evaluation tool, such that we will be able to systematically gauge our work performance. But how can we apply a measurable system? The answer to this is we will need to set up a metric system for sampling survey or field studies with a tolerant yet more accurate fuzzy data.

A number of studies discussed the need for better incorporating time in theoretical models and research designs, e.g. George and Jones (2000), Ancona *et al.* (2001) and Wright (2002) in the management literature. Others focussed on the ways in which people in organizations manage their time, and on ways in which these efforts can be improved for the time management. Samuels (2008) demonstrated that most school leaders hope that at least half of their working day is spent on meaningful interactions with teachers and students, but that is not likely. Leaders spend only a third of their day, or less, on tasks that involve interaction with students and teachers. And often, the contact with them was too short and unfocussed to lead to actual instructional improvement. In this research, we are going to investigate the effectiveness of leaders' management and efficiency of time allocation through the application of fuzzy set theory.

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On the other hand, many efforts have been made on ranking a set of fuzzy data. For instance, Liu *et al.* (2008) provide a new ranking procedure that is consistent with the preference of the conservative investors. Their ranking procedure satisfies the axioms of three-order relations for the separable fuzzy data. Ramli and Mohamad (2009) do a comparative analysis of research methods in ranking fuzzy numbers. Kumar *et al.* (2010) propose a RM approach for ranking of generalized trapezoidal fuzzy numbers. However, most methods are not developed for considering the evaluation problems. This implies that the fuzzy numbers ranked by these methods are not consistent with the preference of the managers.

Given the very nature of the topic, one would have expected that studies of time management would have looked at how people plan and execute their activities within a given time interval, and that researchers would have investigated plan-action discrepancies as a function of dynamic events, time budgets, etc. However, most research studies have used cross-sectional designs and measurement instruments that emphasize stable rather than dynamic aspects of time management behavior. In our view, future research could profit much from dynamic approaches to theory building and research (cf. Nguyen and Wu, 2006a; Nguyen *et al.,* 2011).

There are more and more researches focus on the fuzzy statistical analysis and applications in the social science fields, such as Wu and Hsu identified the model construction through qualitative simulation; Wang and Wu proposed fuzzy statistical testing method to discuss the stability of Taiwan short-term money demand function; Wu and Sun, demonstrated the concepts of fuzzy statistic and applied it to social survey; Tseng and Wu used fuzzy regression method of coefficient estimation to analyze Taiwan monitoring index of economic. For an extensive treatment of the theory of fuzzy statistics the interested reader may refer to Nguyen *et al.* (2011).

Furthermore, in many fields, such as human language, thought, and decision making where categorization (or ranking) is vague and non-quantitative, of which many are even non-specific preferences, (it becomes blur) significant data may slip through our fingers easily. Little literatures have considered the soft computing with the statistics of actual and expected time for people's time access.

2. Literature review

Time management involves the process of determining needs, setting goals to achieve these needs, as well as prioritizing and planning tasks required to achieve these objectives. Macan (1996) proposed a technique for effective time use, especially having enough time to accomplish the many tasks required, planning, and allocating time. Kaufman-Scarborough and Lindquist (1999) suggested a valuable resource to undergraduate and graduate students interested in the applications of production management under fuzziness. Strongman and Burt (2000) intended to maximize intellectual productivity, ways to assess the relative importance of activities through the development of a prioritization plan. The book *Production Engineering and Management* under Fuzziness Series: Studies in Fuzziness and Soft Computing (edited by Kahraman and Yavuz, 2010) represents all areas of production management and are organized to reflect the natural order of production management tasks. In this book, special attention is given to applicability and wherever possible, numerical examples are presented.

Time management behaviors comprise: time assessment behaviors, which aim at awareness of here and now or past, present, and future and self-awareness of one's time use (attitudes, cognitions, which help to accept tasks and responsibilities that fit within the limit of one's capabilities; planning behaviors, such as setting goals, planning tasks, prioritizing, making to-do lists, and grouping tasks (e.g. Macan, 1996; Lee *et al.*, 2012), which focus on an effective use of time; monitoring behaviors, which emphasize on observing one's use of time while performing activities, generating a feedback loop that allows a limit to the influence of interruptions by others, e.g. Zijlstra *et al.* (1999) and Wu *et al.* (2012).

Based on the above discussion, we propose an idea of time management as "behaviors that aim at achieving an effective use of time while performing certain goal-directed activities" in this research. This concept emphasize on that the efficient evaluation of time management do mainly depend on the difference of time expectation with time observation (realization).

The time management questionnaires (TMQ) included factor items on attitudes tendency toward time management, e.g. "do you feel you are in charge of your own time, by and large?" and on planning the allocation of time. The scale consisted of three factors, namely short-range planning, long-range planning, and time attitudes. Williams *et al.* (1995) included all three scales in a study but did not present internal consistency values or other psychometric information about the TMQ.

Adams and Jex (1999) found that setting goals and priorities as well as preference for organization were positively related to perceived control, whereas mechanics of time management were negatively related to perceived control of time. Claessens *et al.* (2004) used a different time management scale to test the mediation model over time. A planning scale was used instead. This study also revealed partial mediation of control of time. In conclusion, these studies found some support for process model that hypothesized perceived control of time to fully mediate between time management behaviors and job-and person-related outcomes.

Time management activity has been studied in relation to several other outcome variables. Some studies have looked into effects on proximal variables, such as accurately estimated time duration, and spent time on high-priority tasks, see Francis-Smythe and Robertson (1999). Other studies have examined effects on performance in work and academic settings, such as job performance, academic performance, (see Burt and Kemp, 1994) and total study habits score. Adams and Jex (1999) and Francis-Smythe and Robertson (1999) have investigated the effects on attitudinal and stress-related outcomes, such as perceived control of time; job satisfaction; job-related and somatic tension. As for emotional exhaustion, Peeters and Rutte (2005) found that time management moderated the relation between high demands and low autonomy on the one hand, and emotional exhaustion on the other.

The proximal outcomes, time estimation, and spending time on high-priority tasks were positively affected. Francis-Smythe and Robertson (1999) concluded that participants who perceived themselves as practicing time management behaviors estimated the expected time durations more accurately than those who did not, but tended to underestimate time commuting. There appeared to be a difference between the academic and job-related performance outcomes. In conclusion, research has found positive effects of time management behavior on proximal outcomes, performance, and stress-related outcomes. However, the results obtained for performance appear to be the weakest in the past studies.

3. Statistical analysis with soft computing

3.1 Questionnaire with fuzzy set theory

After the research of Fuzzy Graphic Rating Scale (FGRS) presented by Hesketh *et al.* (1988), Costas *et al.* (1994) furthered to choose 100 university students as a sample of the research, they found that FGRS fits to the feature of human psychology. Herrera and Herrera-Viedma (2000) presented the steps of linguistic decision analysis under linguistic information. Their statements believe that there are certain degrees of possibilities to express linguistics based on fuzzy number, but it should be reconsidered that if the response produce the identical fuzzy number. Liu and Song develop 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. Carlsson and Fuller (2000a, b), Chiang *et al.* (2000) and Herrera and Herrera-Viedma (2000) have discussed many concepts about the computation of fuzzy linguistic and these concepts are worthy to broadcast.

In the research of social science, the sampling survey is always used to evaluate and understand public opinion on certain issues. The traditional survey forces people to choose fixed answer from the survey, but it ignores the uncertainty of human thinking. For instance, when people need to choose the answer from the survey which lists five choices including "Very satisfactory," "Satisfactory," "Normal," "Unsatisfactory," and "Very unsatisfactory" despite of the fact that the answer of the question is continual type, we may be only allowed to choose one answer. It limits the flexibility of the answer and forces people to choose fixed answers. Based on associated research archives from previous statements, we can have the following inference: the methods of traditional statistical analysis and measurement used in public consensus are incomplete and not enough. Based on the fuzzy feature of human thought, quantifying the measurement of public consensus processed by fuzzy number should be seriously considered and discussed. The measurement of attitudes and feelings based on the fuzzy set theory is a very critical method in recent years.

If people 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.

3.2 The nature of fuzzy answering

Since many replies from sampling survey are illustrated with vague, uncertainty, and incomplete type, the information itself can be grouped into two types: continuous and discrete. In this section we will give brief definitions with fuzzy data.

Continuous fuzzy data can be classified into several types, such as interval, triangular, trapezoid numbers, and exponential, etc. The logic of interval analysis that follows is one of certain containment. For example, the sum of two intervals certainly contains the sums of all pairs of real numbers, one from each of the intervals. We draw the definitions of interval arithmetic, based on simple properties of the order relation $\leqslant$ on the real line.

Here let us give the definition for the trapezoid data, which can be seen as the generalized form for the interval and triangular form. A fuzzy number $A = [a, b, c, d]$, defined on the universe set U of real number R with its vertex $a \leqslant b \leqslant c \leqslant d$, is said to be a trapezoidal fuzzy number if its membership function is given by (see Nguyen and Wu, 2006b):

$$u_F(x) = \begin{cases} \frac{x-a}{b-a}, & a \leqslant x \leqslant b \\ 1, & b \leqslant x \leqslant c \\ \frac{d-x}{d-c}, & c \leqslant x \leqslant d \\ 0, & \text{otherwise} \end{cases}$$

when $b=c$, we say A is a triangular data; when $a=b$, $c=d$, we say A is an interval-valued data.

If people can express the degree of their feelings by using membership functions, the answer presented will be closer to real human thoughts and thus we obtain the concealed entrance to more data. But unfortunately scholars disagree in opinion about the construction of continuous fuzzy data. The core of all the questions is fuzzy data determined by its membership function, but the construction of membership function is quite subjective. To reflect this, we ask the respondents to determine the membership function based on the GSP software.

Figure 1 is the image of fuzzy questionnaire which is about the prime time for marriage. 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 $28 \sim 30$. $\overline{CD}$ represents the desire for marriage falls continuously from 30 until it reaches 35.

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 change automatically. Figure 2 is a special case of trapezoid when point B equals to point C. It represents the prime time for marriage is only 30. Figure 1 shows the prime time for marriage is $28 \sim 30$.

There are probably three types of fuzzy data: the first is trapezoid, the second is triangular, and the third is interval-valued type. Figure 2 illustrates these three kinds of fuzzy data.

3.3 Measurement with fuzzy data

A trapezoid fuzzy set can be viewed as a continuous fuzzy set, which further reveals uncertain events. When a sample of trapezoid data are presented, we are interested in scaling its value on the real line. In some practical applications, however, it is

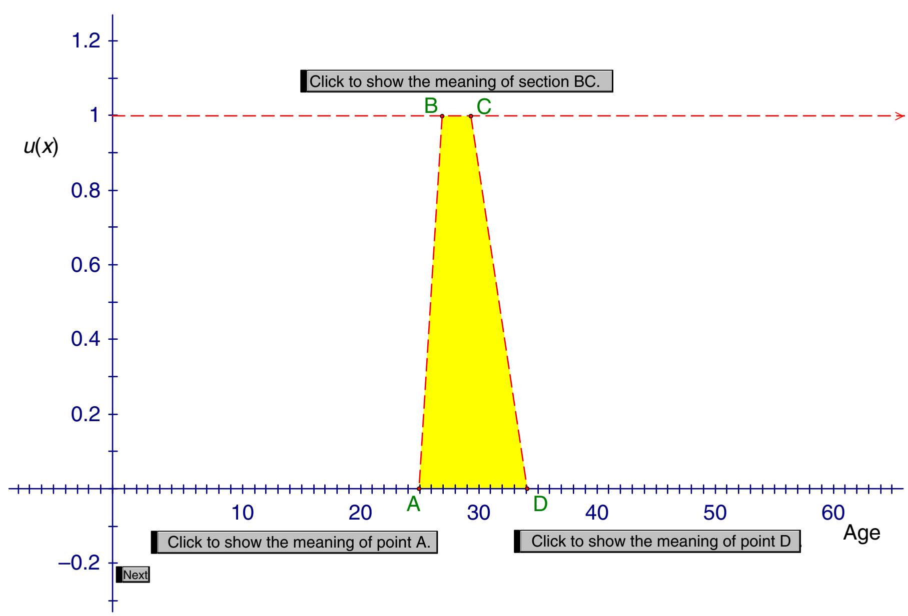

Figure 1.
A fuzzy answer for the expected marriage age

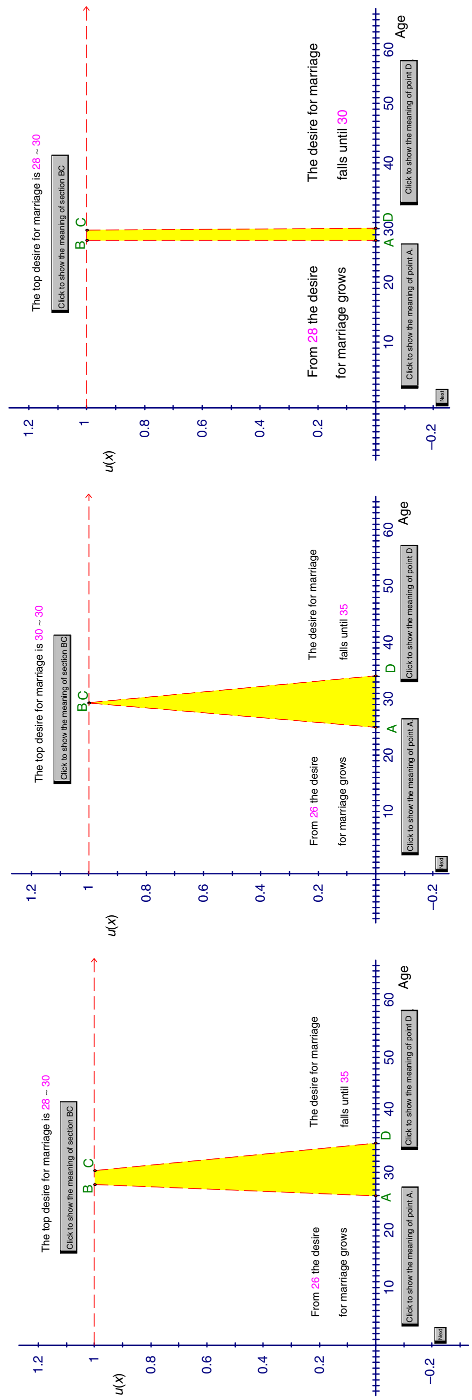

Figure 2.
Fuzzy observation for idea marriage year

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 and/or of a sound can be measured in watts as well as logarithmic scale.

When we consider the reasonable and meaningful conditions to map trapezoid data into the real line, we need to identify two conditions. This means that the transformation data 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 trapezoid 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 a rescaling, the numerical values of the quantity x is not uniquely determined.

Definition 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 value RA of $A=[a,b,c,d]$ is defined as:

$$RA = cx + \frac{\|A\|}{2\ln(e+\|A\|)}$$

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

Note that for convenience we will write; $\|A\| = (a+b+c+d)/4$, if A is a trapezoid; $\|A\| = (a+b+c)/3$, if A is a triangle; $\|A\| = (b+c)/2$, if A is an interval.

Example 1. Let $A_1=[2,2,3,3]$, $A_2=[1,1,4,4]$, $A_3=[1,2.5,2.5,4]$, $A_4=[1,2.5,2.5,8]$, $A_5=[1,2,3,4]$ and $A_6=[1,2,3,8]$ be the fuzzy data. According to Definition 1 we illustrate the defuzzification values on the following Table I.

However, there are few literatures and definitions appeared in the measurement system. In this section, we will propose a well-defined distance for trapezoid data.

Definition 2. Let $A_i=[a_i,b_i,c_i,d_i]$ be a sequence of 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 distance between the trapezoid fuzzy number A_i and A_j is defined as:

$$d(A_i, A_j) = \left|cx_i - cx_j\right| + \left|\frac{\|A_i\|}{2\ln(e+\|A_i\|)} - \frac{\|A_j\|}{2\ln(e+\|A_j\|)}\right|$$

Example 2. Let the fuzzy data be $A_1=[2,2,3,3]$, $A_2=[1,1,4,4]$, $A_3=[1,2.5,2.5,4]$, $A_4=[1,2.5,2.5,8]$, $A_5=[1,2,3,4]$ and $A_6=[1,2,3,8]$. According to Definition 2 we reveals their distance on the following Table II.

The distance states the gap between observed data and expected value; the smaller the distance demonstrates that observed data are more fit for the expected values.

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

Definition 3. Index of efficiency between ideal and actual event (*IOE*).

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 ideal data are defined as:

$$IOE = e^{-\left(\frac{|cx_o - cx_e|}{2\ln(e+|cx_e|)} + \left|\frac{\|O\|}{2\ln(e+\|O\|)} - \frac{\|E\|}{2\ln(e+\|E\|)}\right|\right)}$$

where cx_o and cx_e stand for the centroid on x-axis of the observed and expected value.

Fuzzy data	cx	$\frac{\|A\|}{2\ln(e+\|A\|)}$	RA
$A_1=[2,2,3,3]$	2.5	0.42	2.92
$A_2=[1,1,4,4]$	2.5	0.89	3.39
$A_3=[1,2.5,2.5,4]$	2.5	0.55	3.15
$A_4=[1,2.5,2.5,8]$	3.83	0.99	4.82
$A_5=[1,2,3,4]$	2.5	0.68	3.18
$A_6=[1,2,3,8]$	3.79	1.07	4.86

Table I. Defuzzification for fuzzy data

$d(A_i, A_j)$	$A_1=[2,2,3,3]$	$A_2=[1,1,4,4]$	$A_3=[1,2.5,2.5,4]$	$A_4=[1,2.5,2.5,8]$	$A_5=[1,2,3,4]$	$A_6=[1,2,3,8]$
$A_1=[2,2,3,3]$	0	0.47	0.13	1.90	0.31	1.68
$A_2=[1,1,4,4]$		0	0.34	1.43	0.21	1.47
$A_3=[1,2.5,2.5,4]$			0	1.77	0.13	1.81
$A_4=[1,2.5,2.5,8]$				0	1.64	0.12
$A_5=[1,2,3,4]$					0	1.68
$A_6=[1,2,3,8]$						0

Table II. Distance for fuzzy data

The higher value of IOE indicates a better efficient time management. If $IOE = 1$, we say the event is absolutely efficient in the time management. If $IOE = 0$, 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, we ask for 40 managers from the median-sized company from Taipei City to reply the questionnaires: Ages from 30 to 60, male 29 and female 11. From the result of the sampling survey, we find that they spend 26$\sim$38 hours a week at the management work. This includes: 20$\sim$25 hours for the office hours, 2-5 hours for extended work after, 2$\sim$4 hours for leisure time, and 2$\sim$4 hours for standby. Table III demonstrates a statistical result for this field studies.

Use Definitions 2 and 3 at Section 3.3, we can compute the gap for actual and expected working time. Table IV indicates the distance and index of efficiency for three types of time allocation.

From Table IV 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 conclusion that the managers' innovative/development skill is closest to ideal. It also demonstrates that the level is highly efficient.

On the other hand, it has greater individual differences thus displaying polarization. The time spent on public relations leadership is less and the biggest gap indicates the poor performance.

4.2 A non-parametric test with fuzzy data

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

Table III.
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 IV.
The distances and index of efficiency the three types of management

	Observe	Expected	$d(o_i, e) = \lvert c_o - c_e\rvert + \left\lvert \frac{\lVert o\rVert}{2\ln(e+\lvert c_o\rvert)} - \frac{\lVert e\rVert}{2\ln(e+\lvert c_e\rvert)} \right\rvert$	Efficiency Index (IOE) $= e^{-\left(\frac{\lvert c_o - c_e\rvert}{2\ln(e+\lvert c_e\rvert)} + \left\lvert \frac{\lVert O\rVert}{2\ln(e+\lVert c_o\rVert)} - \frac{\lVert e\rVert}{2\ln(e+\lVert c_e\rVert)} \right\rvert\right)}$
Administration	[21, 29]	[19, 22]	*5.11*	$e^{-1.44} = 0.24$
Innovative/ development	[15, 20]	[16, 20]	*0.64*	$e^{-0.25} = 0.78$
Public relations	[5, 8]	[7, 9]	*1.70*	$e^{-0.57} = 0.57$

Assumption: Two fuzzy observations each has n subjects. Let i denote the particular subject that is being referred to and the first fuzzy observation measured on subject i be denoted by A_i and second fuzzy observation by B_i.

H0. The two populations have the same mean, i.e. *H0*: $median(A) = median(B)$

Testing statistic: the Wilcoxon signed-rank statistic W^+ is computed by ordering defuzzification data RA_i, RB_i from smallest to largest, the rank of fuzzy samples A_i, B_i, and is given a rank of r_i. In this situation assign each tied value the mean of the rank positions. For example, if three smallest are all equal, rank them 1, 2, and 3, but assign each a rank of $(1+2+3)/3 = 2$.

Denote:

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

The Wilcoxon signed rank statistic W^+ is defined as:

$$W^+ = \sum_{i=1}^{n} I_i^+ r_i$$

and W^- is defined as:

$$W^- = \sum_{i=1}^{n} I_i^- r_i$$

to simplify notation, we use the smaller of the two T, i.e. $T = \min(W^+, W^-)$.

Decision rule: reject *H0* if $T \leqslant W_\alpha$ (the critical value under a α-level significance). A survey showed wives spend more time on housework than husbands do of each spouse per week. Such that, 11 couples are invited to do a fuzzy questionnaire about the time spent on housework per week. The calculations for obtaining the test statistics are summarized in Table V:

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

Couple	Husband (A_i)	Wife (B_i)	$R(A_i)$	$R(B_i)$	$R(A_i) - R(B_i)$	Rank of $\lvert RA_i - RB_i \rvert$
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

Table V.
Housework time

M_A is the median of the time which female spend on housework per week; M_B the median of the time which male spend on housework per week, and *H0*: $M_A = M_B$ vs $M_A > M_B$.

Under the $\alpha = 0.05$ level of significance, since $W^+ = 13 < W_{0.05} = 14$, we reject *H0*. That is wives spend more time on housework than husbands do.

5. Conclusions

Soft computing techniques grow as a new discipline from the necessity to deal with vague samples and imprecise information caused by human thought in certain experimental environments. In this paper, we made an attempt to link the gap between the binary logic based on multiple choice survey with a more complicated yet precise fuzzy membership function assessment.

We carefully revealed on how to use fuzzy statistics in people's time management effectiveness of fuzzy time allocation and management assessments. The proposed *IOE* is a useful measurement for evaluation. Empirical studies demonstrate how to measure fuzzy data that can deal with trapezoid, triangular, and interval-valued data simultaneously and to perform the non-parametric testing hypothesis.

The panorama proposed above can anticipate a more sophisticated and detailed interpretations of our data than the conventional ones, especially when our data could not exhibit a 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) We can further our research on data simulation so that we can understand features of the fuzzy linguistic, multi-facet assessment, and the balance of the moving consensus. Moreover, the choice of different α-cut will influence the statistical result. An appropriate criterion for selecting significant α-cut should be investigated in order to reach the best common agreement of human beings.

(2) To avoid inappropriate implementation, it is an urgent project to provide people with a time management training course to assist them to work efficiently.

(3) There are other types of membership functions we could explore in the future. For the fuzzy mode of continuous type, we can extend the uniform and triangular types of membership functions to non-symmetric or multiple peaks types.

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About the authors

Professor Berlin Wu received the PhD Degree in Statistics from the Indiana University – Bloomington, Indiana (1988). Dr Wu is currently a Professor in the Department of Mathematical Sciences at the National Chengchi University, Taiwan. He was award by Fulbright Scholarship 1997, and was a Distinguished Research Professor Prizes of National Chengchi University, 2002 and 2004. His current research interests include non-linear time series analysis, fuzzy statistical analysis, and discovering various forecasting techniques with soft computing methods.

Professor Hung T. Nguyen, PhD Mathematics, 1975 – Emeritus Professor of Mathematical Sciences, New Mexico State University, USA, is an Adjunct Professor of Economics at the Chiang Mai University, Thailand. Awards and recognition: Chair of Fuzzy Theory (1992-1993): Tokyo Institute of Technology, Japan. Westhafer Award for Excellence in Research and Creativity (2000): New Mexico State University, Las Cruces. Distinguished Lukacs Professor of Statistics (Spring 2002): Bowling Green State University, Ohio. Distinguished Faculty Fellow (Summers 2002 and 2003): American Association of Engineering Education (ASEE), Summer Faculty Research Programs. Fellow of the International Fuzzy Systems Association (April 2007). Life Fellow of Japan Society of Management Engineers (October 2012). Current research interests: statistics for econometrics: Copulas, heavy tailed distributions, and maximum entropy inference.

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