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EFFICIENCY EVALUATION IN TIME MANAGEMENT FOR SCHOOL ADMINISTRATION WITH FUZZY DATA

Berlin Wu[1], Mei Fen Liu[2] and Zhongyu Wang[3]

[1]Department of Mathematical Sciences
National ChengChi University
No. 64, Sec. 2, ZhiNan Rd., Wenshan District, Taipei City 11605, Taiwan
berlin@nccu.edu.tw

[2]Department of Education Policy and Administration
National Chi Nan University
No. 1, University Rd., Puli, Nantou County 545, Taiwan
molly@tc.edu.tw

[3]School of Management
Harbin Institute of Technology
No. 13, Fayuan Street, Nan Gang District, Harbin 150001, P. R. China
wangzhy@hit.edu.cn

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Abstract. *How to evaluate the performance of school administration has become more and more important during the recent years. In this paper, soft computing technique and fuzzy statistical tool are used to evaluate the school performance of the time management. The proposed metric system helps us to assess the distance among fuzzy data. The indices of efficiency between observed time and ideal time are also presented. Empirical studies show that the use of interval data is more realistic and reasonable in the social science research. Finally, suggestions are made for the further studies.*
Keywords: School administration, Efficiency evaluation, Fuzzy statistics, Index of efficiency, Time management

1. Introduction.

Due to the global educational reform, how to promote the quality of education has become an important issue. *As is the principal, so is the school* (Valentine and Bowman [1]). School leaders have a decisive influence on school management. They are responsible for school development and prospects. How to make impossible become possible by effectively managing the time is extremely important in leadership performance.

Curriculum and teaching are the cores of education at school. However, Peterson [2] stated that the leaders at elementary schools spend less than 7 percent of their time on the courses, and less than 5 percent in the classroom. Morris, Crowson, Poter-Gehrie and Hurwitz [3] found that most leaders spend less than 9 percent of their time on class visiting. Murphy [4] reviewed other literature and finds that school administrative leaders spend most of their time on students' discipline, parental relationship, school facilities, and school financial management, but not on school curriculum. Horng, Klasik and Loeb [5] claimed that the leaders at elementary schools spend 25.3 percent of their time on administration, 20.9 percent on organizational management and 17.3 percent on the internal relationship. Samuels [6] claimed that most leaders hope that at least half their working day is spent on meaningful interactions with teachers and students, but that is impossible. Leaders spend only a third of their day, or less, in tasks that involve interaction with students and teachers. And often, the contact with them is too short and unfocused to lead to actual instructional improvement.

However, we cannot talk about promoting the quality of school administration without tackling the problem of using efficient evaluation tool that administrators are able to systematically gauge work performance. No matter what business we are in, implementing an efficient evaluation system is an important part of it. However, how can we apply a measurable system? The answer to this is that we need to set up a metric system from the sampling survey or field studies.

Most educational studies do not consider the measurement on the realistic statistics and expect time for school leaders' business hours. Moreover, very few use fuzzy statistics to analyze the interval data. Xu and Wu [7] have discussed correlation measurement and causality analysis between two variables in the science research work.

If we have an efficient measurement, we will be able to systematically gauge work's performance. The evaluation work by comparing the leaders' own goals and objectives is what we want to accomplish. Once we have the measurement rules, we will have a better outline or guides on how we can base our search for using appropriate methods.

The plan of the paper is as follows. In Section 2, we provide with fuzzy statistical methods and framework that form our focus of interest. In Section 3 we propose a heuristic evaluation on measuring distance for fuzzy data and set up the formula for the efficiency of time management. Section 4 is illustrated with an empirical study. An interesting feature of this empirical study is that our proposed measurement system can more accurately reflect the efficiency of time management for school leaders than that of the traditional ones. Section 5 provides a summary and concluding remark.

2. **Statistical Analysis with Fuzzy Data.**

2.1. **Fuzzy questionnaire.** The question we will ask is what we need in statistical tools to include in the evaluation. Since evaluation needs to be aligned with the same logic base, there should also be significant differences between the metrics that they are using. The key to this is to find a well-established evaluation system that goes along with our own goals and objectives.

After the research on FGRS (Fuzzy Graphic Rating Scale) presented by Hesketh, Pryor, Gleitzman and Hesketh [8], Costas, Maranon and Cabrera [9] furthered to select 100 university students as a sample of the research, they found that FGRS really fits to the feature of human psychology.

Herrera and Herrera-Viedma [10] presented the steps of linguistic decision analysis under linguistic information. They believe 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 and Song [11] developed one type of measurement whose linguistic is similar to semantic proximity. Based on the similarity of linguistic concept, they presented a formula of fuzzy association degree. Liu and Song [11] used the information of botany as an example to illustrate and analyze the categorical similarity of rare plant in the ecology. Carlsson and Fuller [12], Carlsson and Fuller [13], Chiang, Chow and Wang [14], Herrera and Herrera-Viedma [10], Dubois and Prade [15] had discussed many concepts about the computation of fuzzy linguistic and these concepts are worthy to broadcast.

Based on associated research archives from previous statements, we can infer the following two points:

(i) 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 with fuzzy number should be seriously considered and discussed.

(ii) The measurement of attitudes and feelings based on the fuzzy theory was a very critical method in the past years. There are many associated scholar arenas in this type of research. However, educational and psychological research is still not so many as other research fields. In conclusion, the theoretic research on fuzzy mode and experimental discussion presented in this paper is a possible solution owing to its importance.

2.2. **Statistical analysis with fuzzy data.** 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", "Very unsatisfactory", and the answer to the question is continual type, so we may be only allowed to choose one answer. It limits the flexibility of the answer and forces people to choose fixed answers. When the survey proposes to have the answer for sleeping hours of a person, it will be difficult to describe the feeling or understanding reasonably unless the fuzzy mode is adopted.

Traditional statistics deals with single answer or certain range of the answer through sample survey, and unable to sufficiently reflect the thought of an individual. If people 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, collecting the information based on the fuzzy mode should be more reasonable. In the consideration for the question related with fuzzy property, the information itself had the uncertainty and fuzzy property. The following are the definitions of discrete fuzzy mode and continuous fuzzy number. The discrete fuzzy mode is simpler than continuous fuzzy mode. The computation of discrete number is easier than the continuous one.

Since many sampling surveys are closely related to fuzzy thinking while the factors of set can be clearly grouped into many categories, it will be useful if we apply discrete fuzzy number to the public consensus.

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

Definition 2.1. *Fuzzy Mode (data with multiple values)*

Let U be the universal set (a discussion domain), $L = \{L_1, L_2, \cdots, L_k\}$ a set of k-linguistic variables on U, and $\{FS_i, i = 1, 2, \cdots, n\}$ a sequence of random fuzzy sample on U. For each sample FS_i, assign a linguistic variable L_j a normalized membership m_{ij} $\left(\sum_{j=1}^{k} m_{ij} = 1\right)$, let $S_j = \sum_{i=1}^{n} m_{ij}$, $j = 1, 2, \cdots, k$. Then, the maximum value of S_j (with respect to L_j) is called the fuzzy mode (FM) of this sample. That is $FM = \left\{L_j \,\middle|\, S_j = \max_{1\le i\le k} S_i\right\}$.

Note: A significant level α for fuzzy mode can be defined as follows: Let U be the universal set (a discussion domain), $L = \{L_1, L_2, \cdots, L_k\}$ a set of k-linguistic variables on U, and $\{FS_i, i = 1, 2, \cdots, n\}$ a sequence of random fuzzy sample on U. For each sample FS_i, assign a linguistic variable L_j a normalized membership m_{ij} $\left(\sum_{j=1}^{k} m_{ij} = 1\right)$, let $S_j = \sum_{i=1}^{n} I_{ij}$, $j = 1, 2, \cdots, k$, $I_{ij} = 1$ if $m_{ij} \geq \alpha$, $I_{ij} = 0$ if $m_{ij} < \alpha$, α is the significant level. Then, the maximum value of S_j (with respect to L_j) is called the fuzzy mode of this sample. That is $FM = \left\{ L_j \middle| S_j = \max_{1 \leq i \leq k} S_i \right\}$. If there are more than two sets of L_j that reach the conditions, we say that the fuzzy sample has multiple common agreements.

Definition 2.2. Fuzzy Mode *(data with interval values)*
Let U be the universal set (a discussion domain), $L = \{L_1, L_2, \cdots, L_k\}$ a set of k-linguistic variables on U, and $\{FS_i = [a_i, b_i], a_i, b_i \in R, i = 1, 2, \cdots, n\}$ be a sequence of random fuzzy sample on U. For each sample FS_i, if there is an interval $[c, d]$ which is covered by certain samples, we call these samples as a cluster. Let MS be the set of clusters which contains the maximum number of sample, then the fuzzy mode FM is defined as

$$FM = [a, b] = \{\cap[a_i, b_i] \,|[a_i, b_i] \subset MS\}.$$

If $[a, b]$ does not exist (i.e., $[a, b]$ is an empty set), we say this fuzzy sample does not have fuzzy mode.

Suppose eight voters are asked to choose a chairman from four candidates. Table 1 is the result from the votes with two different types of voting: traditional response versus fuzzy response.

Table 1. Response comparison for the eight voters

item / *voter*	*traditional response*				*fuzzy response*			
	A	*B*	*C*	*D*	*A*	*B*	*C*	*D*
1		√				*0.7*	*0.3*	
2	√				*0.5*		*0.4*	*0.1*
3				√			*0.3*	*0.7*
4			√		*0.4*		*0.6*	
5		√				*0.6*	*0.4*	
6				√	*0.4*		*0.2*	*0.6*
7		√				*0.8*	*0.2*	
8			√				*0.8*	*0.2*
Total	*1*	*3*	*2*	*2*	*1.3*	*2.1*	*3.2*	*1.6*

From the traditional voting, we can find that there are three persons voting for B. Hence the mode of the vote is B. However, from the fuzzy voting, B only gets a total membership of 2.1, while C gets 3.2. Based on traditional voting, B is elected the chairperson, while based on the fuzzy voting or membership voting, C is the chairperson. The voters' preference is reflected more accurately in fuzzy voting, C deserves to be the chairperson more than B does.

Definition 2.3. Fuzzy expected value *(data with multiple values)*
Let U be the universal set (a discussion domain), $L = \{L_1, L_2, \cdots, L_k\}$ be a set of k-linguistic variables on U, and $\{FS_i = \frac{m_{i1}}{L_1} + \frac{m_{i2}}{L_2} + \cdots + \frac{m_{ik}}{L_k}, i = 1, 2, \ldots, n\}$ be a sequence

of random fuzzy sample on U, m_{ij} $\left(\sum_{j=1}^{k} m_{ij} = 1\right)$ *is the memberships with respect to* L_j.

Then, the fuzzy expected value was defined as $E(X) = \frac{\frac{\sum_{i=1}^{n} m_{i1}}{n}}{L_1} + \frac{\frac{\sum_{i=1}^{n} m_{i2}}{n}}{L_2} + \cdots + \frac{\frac{\sum_{i=1}^{n} m_{ik}}{n}}{L_k}$.

Definition 2.4. *Fuzzy expected values (data with interval values)*

Let U *be the universe set, and* $\{FS_i = [a_i, b_i], a_i, b_i \in R, i = 1, 2, \cdots, n\}$ *be a sequence of random fuzzy sample on* U. *Then the fuzzy expected value is defined as* $E(X) = \left[\frac{\sum_{i=1}^{n} a_i}{n}, \frac{\sum_{i=1}^{n} b_i}{n}\right]$.

Example 2.1. *Let the time series* $\{X_t\} = \{0.8, 1.6, 2.8, 4.2, 3.6, 3.1, 4.3\}$ *be the variation of a stock's value with 7 days. We can see the total range is* $4.3 - 0.8 = 3.5$. *We give an equal interval partition for* $[0.8, 4.3]$, *say* $U = \{(0,1), (1,2), (2,3), (3,4), (4,5)\}$. *The linguistic variable with respect the intervals are very low* $= L_1 \propto (0, 1]$, *low* $= L_2 \propto (1, 2]$, *medium* $= L_3 \propto (2, 3]$, *high* $= L_4 \propto (2, 3]$, *very high* $= L_5 \propto (2, 3]$; *where* $\propto$ *means "respect to". The medium for each partition are* $\{m_1 = 0.5, m_2 = 1.5, m_3 = 2.5, m_4 = 3.5, m_5 = 4.5\}$. *Since* X_1 *falls between 0.5 and 1.5.* $\frac{1.5-0.8}{1.5-0.5} = 0.7 \in L_1$, $\frac{0.8-0.5}{1.5-0.5} = 0.3 \in L_2$ *the fuzzy value of* X_1 *is* $F_1 = (0.7, 0.3, 0, 0, 0)$. *Similarly, we get the other fuzzy samples as follows.*

Table 2. The fuzzy values for time series $\{X_t\}$

	Very low = 1	*Low = 2*	*Medium = 3*	*High = 4*	*Very high = 5*
F_1	*0.7*	*0.3*	*0*	*0*	*0*
F_2	*0*	*0.9*	*0.1*	*0*	*0*
F_3	*0*	*0*	*0.7*	*0.3*	*0*
F_4	*0*	*0*	*0*	*0.3*	*0.7*
F_5	*0*	*0*	*0*	*0.9*	*0.1*
F_6	*0*	*0*	*0.4*	*0.6*	*0*
F_7	*0*	*0*	*0*	*0.2*	*0.8*

The fuzzy expected value for the time series is

$$\begin{aligned} E(X) = & \frac{0.7/7}{1} + \frac{(0.3+0.9)/7}{2} + \frac{(0.1+0.7+0.4)/7}{3} \\ & + \frac{(0.3+0.3+0.9+0.6+0.2)/7}{4} + \frac{(0.7+0.8+0.1)/7}{5} \\ = & \frac{0.1}{1} + \frac{0.17}{2} + \frac{0.17}{3} + \frac{0.33}{4} + \frac{0.23}{5} \end{aligned}$$

3. **Ordering and Operation with Fuzzy Data.** An interval-valued fuzzy set can be viewed as a continuous fuzzy set, which further represents uncertain matters. For instance, in students' GPA we use the linguistic value A, B, C and F to evaluate a student's performance, where A represents a score of 80-100, B represents 70-79, C represents 60-69, and F represents below 60, to stand for the score of 100. Traditionally, we think that the higher scores the student gets, the better performance he or she has. Does a student who gets a grade of 85 have better performance than another who gets 75? It does not seem always true.

When a sample of interval-valued fuzziness is available, we have to consider the calculation for intervals, referring to Nguyen and Wu [16] for interval calculations. However, there are still few references that discuss the definition for the measure and its operation. In this section, we will propose a well-defined measurement system as well as its operation on the interval data.

First, we represent the interval with $(c_i; r_i)$, with c being the center and r being radius. In this way, the interval distance can be considered as the difference of the center plus the difference of the radius. The difference of the center can be seen as the difference in location, and the difference of the radius can be seen as the difference in scale. However, in order to lower the impact of the scale difference on the location difference, we take the ln value of the scale difference, and then plus 1 to avoid the ln value to be negative.

3.1. **Order the fuzzy data.**

Definition 3.1. *Defuzzification for a fuzzy number on R*

Let $x = [a, b]$ $(a \neq b)$ be an interval fuzzy number on U. Then the defuzzification number Rx of $[a, b]$ is defined as

$$Rx = \frac{a+b}{2} + \left(1 - \frac{\ln(1 + |b-a|)}{|b-a|}\right);$$

(Note that if $a \to b$, the interval converges to a real number, then Rx converges to $\frac{a+b}{2}$).

Example 3.1. *Let $x_1 = [2, 3]$, $x_2 = [1.5, 3.5]$, $x_3 = [1, 4]$, $x_4 = [2, 3.5]$. Then,*

$$Rx_1 = 2.5 + \left(1 - \tfrac{\ln(1+1)}{1}\right) = 2.5 + 0.307 = 2.807,$$

$$Rx_2 = 2.5 + \left(1 - \tfrac{\ln(1+2)}{2}\right) = 2.5 + 0.451 = 2.951,$$

$$Rx_3 = 2.5 + \left(1 - \tfrac{\ln(1+3)}{3}\right) = 2.5 + 0.538 = 3.038,$$

$$RA_4 = 2.5 + \left(1 - \tfrac{\ln(1+1.5)}{1.5}\right) = 2.5 + 0.389 = 2.889.$$

3.2. **Distance among fuzzy data – Fuzzy distance between ideal and realistic data.**

Definition 3.2. *Distance between samples of interval-valued data*

Let U be the universe of discourse. Let $\{x_i = [a_i, b_i], i = 1, 2\}$ be two samples from U, with center $c_i = \frac{a_i+b_i}{2}$, and radius $r_i = \frac{a_i-b_i}{2}$, the distance between the two samples x_1 and x_2 is defined as

$$d(x_i, x_j) = |c_i - c_j| + \left| \frac{\ln(1 + |b_i - a_i|)}{|b_i - a_i|} - \frac{\ln(1 + |b_j - a_j|)}{|b_j - a_j|} \right|$$

Example 3.2. *Let two sets of interval data be $x_1 = [2, 5]$, $x_2 = [3, 7]$. Then $x_1 = (3.5; 1.5)$, $x_2 = (5; 2)$*

$$d(x_1, x_2) = |3.5 - 5| + \ln(1 + |1.5 - 2|) = 1.9$$

The distance illustrates the gap between observed data and expected value. The smaller the distance demonstrates, the more fitting observed data is for the expected values. In order to have a clear picture about the distance between idea and reality, we need the following definitions, for which the value will be standardized constraint on 0 and 1.

Definition 3.3. *Index of efficiency between idea and reality*

Let U be the universe of discourse. Let $OI = (c_o; r_o)$ be the observed data and $EI = (c_e; r_e)$ be the expected data from U. The index of fuzzy distance between observed and ideal data is defined as

$$IOE = e^{-\left(\left|\frac{c_o - c_e}{c_e}\right| + \ln\left(1 + \left|\frac{r_o - r_e}{r_e}\right|\right)\right)}.$$

where c_o and c_e stand for the center of the observed and expected value.

The higher the value of IOE is, the more efficient the time management is. If $IOE = 0$, we see the leadership as no efficient at all. The greater the distance states, the leadership level perceptions and actual elapsed time do not meet, i.e., no efficiency. If $IOE = 1$, the leadership is absolutely efficient in the time management. That means the smaller the distance stated, the leadership level perceptions and actual running time related consistency can show their work efficiency.

4. Empirical Studies.

4.1. **Efficiency of time management for school leaders.** In a field study on the efficiency of school management, we collect 40 questionnaires done by the school leaders around Taiwan. The leaders' ages range from 30 to 60, including 29 male, and 11 female. Most schools are located around the countryside of Taiwan.

In this sampling survey, we find school leaders spend $44 \sim 51$ hours a week in the educational management. Other interesting tasks they spend on are: $37 \sim 41$ hours on the office work, $6 \sim 10$ hours on extended work after school, $3 \sim 6$ hours for leisure time, and $3 \sim 5$ hours to be absent minded. The main traditional tasks of the school leaders, accordingly are the administrative leadership, teaching leadership, and public relation leadership. We find that the school leader spends about 42.3 percent of their time on administrative leadership; 38.1 percent on instructional leadership; while 20.1 percent is spent on public relation leadership. Table 3 shows the statistical result of the sampling survey.

Table 3. Fuzzy answering about the importance of leaderships

	Average rank	*Membership*	*Observative (hours/week)*
administrative leadership	*1.4*	*42.3%*	*21.0-31.6*
instructional leadership	*1.8*	*38.1%*	*15.7-23.2*
public relations leadership	*2.8*	*20.1%*	*4.9-8.2*

As for the school leaders' hours in leading business services allocation, we find that the fuzzy mode is academic time which has the membership of 32.4%, the second is the student affairs which has the membership of 28.1%, once again, the general comptroller, membership of 25.7%, and finally for the personnel, membership of 13.8%. As for the school leaders' hours in leading business object allocation, we find that the fuzzy mean is staff time, 37.9%, the second is students, with a fuzzy mean of 27.5%. Table 4 shows the result.

Table 4. Fuzzy statistics with school leaders' time allocation

Leading Business Services	*Academic affairs 32.4%, Student affairs 28.1%, General comptroller 25.7%, Personnel 13.8%*
Leading Business Object	*Staff 37.9%, Students 27.5%, Parents 17%, Extramural 10.8%, School leader outside 9.3%*

4.2. **Efficiency of time allocation.** Using Definitions 3.2 and 3.3 in Section 3.2, we can compute the gap between observed and expected time. Table 5 illustrates the distances and indices for the three types of leadership.

From Table 5, we can see the distance between observed and expected time. The indices IOE of instructional leadership are a maximum of 0.78. Administrative leadership 0.62 is the second, while public relation leadership is the last with 0.54. From this investigation,

TABLE 5. The distances and efficiency indices for the three types of leadership

	Observed	*Expected*	$d(O,E) = \lvert c_1 - c_2\rvert + \ln(1+\lvert r_1 - r_2\rvert)$	*Efficiency Indices* $(IOE) = e^{-\left(\lvert \frac{c_o - c_e}{c_e}\rvert + \ln\left(1+\lvert \frac{r_o - r_e}{r_e}\rvert\right)\right)}$
Administrative	*[21, 31.6]*	*[18.9, 21.7]*	*7.6*	*0.62*
Instructional	*[15.7, 23.2]*	*[17, 19.5]*	*2.5*	*0.78*
Public relations	*[4.9, 8.2]*	*[8.9, 10]*	*3.6*	*0.54*

we can draw a conclusion that the leaders' instructional leadership skills are closest to ideal. It means that the level is highly efficient, but it has greater individual differences thus displaying polarization. If the time spent on public relation leadership is less, then the poor performance presents the biggest difference.

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 how to use fuzzy statistics in school leaders' time management, effectiveness of fuzzy time allocation, and management assessments. The proposed IOE is a useful measure to evaluate the efficiency of school leaders' time management. The empirical study demonstrates how to apply fuzzy statistical analysis to investigate human thinking.

These points of view proposed in this paper could help researchers have more reasonable interpretations than traditional ones under some uncertain and incomplete situations and solve the problem for constructing continuous fuzzy data. However, there are still some problems we need to investigate in the future:

1. In order not to spend too much time in inappropriate implementation, it is an urgent project to provide school leaders time management training courses to assist them in working efficiently. Let the school leaders have the ability to perform their plans and reach the goals by using the efficient time allocation.
2. We can have further research on data simulation so that we will understand the features of the fuzzy linguistic, multi-facet assessment, and the balance of the moving consensus. Moreover, the choice of different significant α-cut will influence the statistical results. An appropriate criterion for selecting significant α-cut should be investigated in order to reach the best common agreement of human beings.
3. There are other types of membership functions which we could explore in the future. For the fuzzy mode of continuous type, we can extend the uniform and interval types of membership functions to non-symmetric or multiple peaks.

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