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Filtering Items and Calculating Weights of Effective Items for Affective Instruction Evaluation on Higher Education

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Abstract

The traditional affective instruction evaluation on engineering education has contained two separate sections, (I) Section I: Student self-evaluation (include 10 items) and (II) Section II: Evaluation of the instructor's teaching (include 10 items). These 20 items were usually determined by some of the experts or researchers on the affective instructional domain. However, some of items within two sections introduced above could be out of date as time goes by. In another words, some of items might be eliminated, or some of items would become more significant impact due to its availability on affective instruction evaluation. The significant items in evaluation list first were chosen by utilized grey statistics technique so that the significant items for evaluation could be retained and the redundant items were eliminated. Secondly, a fuzzy inference system was applied to compute the weights for each significant left item so as to achieve the weighted-sum value on two separate sections that were mentioned earlier. These methods provide us not only in qualitative but also in quantitative analysis to improve and promote the instruction activity on engineering education for accomplishing the objective of instructions.

1. Introduction

In general, the cognitive instruction evaluation is traditionally used to measure the grade of instruction's examination at college. However, the instructional interaction between instructor and students cannot be shown in this cognitive instruction evaluation. This instructional interactive could executively reflect in the domain of affective instruction evaluation [1][2][3][4][5][6]. The traditional affective instruction evaluation on engineering education has contained some certain items for Section I: student self-evaluation as well as Section II: evaluation of the instructor's teaching. These items were usually determined by some of the experts or researchers on the affective instructional domain [7]. However, some of items within two separate sections could be out of date as time goes by. In another words, some of items might be eliminated, or some of items would become more significant impact due to its availability on affective instruction evaluation. Therefore, two major problems occurred, and they have to be resolved in an appropriate manner. According to an example verified in this paper sampling the investigated 1200 samples' data of affective instruction evaluation [8], this paper thus proposed a fast method for filtering the redundant items within the evaluation list; furthermore, another technique also presented in this paper to calculate the weights of the left items. The significant items in evaluation list first were chosen depending on the appraisal coefficients by utilized grey statistics technique [9][10] through means of grey whiten function so that the significant items could be retained and the redundant items were eliminated. Secondly, a fuzzy inference system [11][12] was applied to compute the weights for each significant left item so as to achieve the weighted-sum value on two separate sections that were mentioned earlier. These methods provide us not only in qualitative but also in quantitative analysis to improve and promote the instruction activity on engineering education for accomplishing the objective of instructions.

2. Clustering Sequence to Certain Grey Number by Applying Grey Statistics

The grey theory is propmoted in recent years. Two major topics [9][10] (grey relational analysis and grey prediction) have been widely applied in the area of engineering or social science. One of assessment method in grey theory i.e. grey statistics is also discussed in literatures in several aspects. The grey statistics method, based on the grey whiten function generating, applied for clustering data within the sequences to a certain attribute that is described by a certain grey number [9][10]. This method can be interpreted to classify a certain attribute for the statistic index; basically, this is the process to transfer a white number to a grey number for classifying the attribute as follows.

Assuming the following indexes: $k = 1,2,3,...,p$ (Index for the Grey Numbers), $j = 1^{\#}, 2^{\#}, 3^{\#}, ..., m^{\#}$ (Statistic Indexes) , and $i = I, II, III, ..., l$ (Statistic Subjects)

Step1: Making a matrix below:

$$D = \begin{array}{c} \\ \\ \\ \\ \\ \\ \end{array}\begin{array}{cccc|c} 1^{\#} & 2^{\#} & & m^{\#} & \\ d_{11} & d_{12} & \cdots & d_{im} & I \\ d_{21} & d_{22} & \cdots & d_{2m} & II \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ d_{l1} & d_{l2} & \cdots & d_{lm} & l \end{array}$$

Step2: Giving the grey whiten functions, and taking an example as shown below.

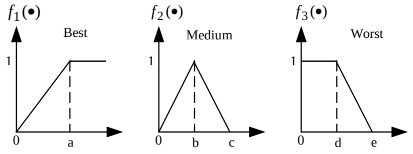

Figure 1

An example for three grey numbers, “Best”, “Medium”, and “Worst”, as shown above

Step3: Finding appraisal coefficients

$$n_{jk} = \sum_{i=1}^{l} f_k(d_{ij}) \cdot N_i \tag{1}$$

where N_i stands for the number of persons in *ith* statistic subject who join this appraisal to evaluate the *jth* statistic index.

Step4: Decision-Making for classifying the attribute to the statistic index according to appraisal coefficients.

3. Fuzzy Inference System for Weights Determination

Fuzzy logic proposed by Zadeh in 1965 [11] is used to establish a mathematical model for describing the linguistic fuzzy information that is belong to the highly nonlinear system in the real world. A fuzzy system [12] actually is relative to fuzzy sets, fuzzy relations, and fuzzy inferences. Fuzzy systems have been widely applied on automatic control, pattern recognition, decision analysis, diagnostic system, forecasting, software engineering, natural language processing, and signal processing since mid-1960 [13][14]. Constructing a model for an unknown system always encountered the problem that the system identification doesn’t work by the certain mathematical model of using differential or difference equations due to its complexity. Therefore, a system model built through the fuzzy logic instead of traditional mathematic equations have advantages about providing better generalization, error tolerance, application fitting, and expert knowledge [15][16][17]. An approximate reasoning (sometimes called generalized modus ponens) could be successfully performed through the means of the fuzzy inference mechanism as shown in many applications during last 50 years. In effect, the process of a fuzzy inference mechanism consists of two stages [14]: (i) cylindrical extension, and (ii) projection; these tow operations actually are done by a fuzzy logic operation called composition operation. Two types of this composition operation are usually applied to an inference procedure: Max-min operation, and Max product operation. The basic structure of a fuzzy system can be classified into four parts [13]: (A) fuzzifier, (B) fuzzy rule base, (C) fuzzy inference engine, and (D) defuzzifier as shown in Fig. 2.

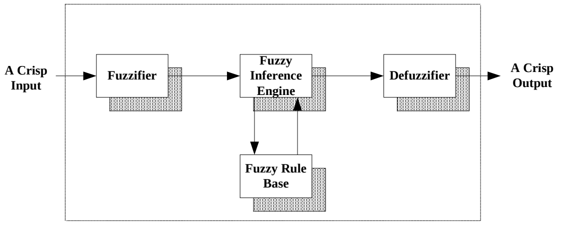

Figure 2

The diagram is the basic structure of fuzzy system.

In fuzzifier part, a fuzzy singleton is usually used in many applications due to its simplification orientation as shown below.

$$\mu_A(x) = \begin{cases} 1 & x = x_0 \\ 0 & x \neq x_0 \end{cases}, \tag{2}$$

where A is a fuzzy set, and $\mu_A(x)$ stands for a membership function of that fuzzy set A.

A fuzzy rule base consists of several appropriate fuzzy rules for certain system. The style of these fuzzy rules could be (a) linguistic fuzzy rule [15], (b) functional fuzzy rule [16][17], or (c) Tsukamoto fuzzy rule [18]. For easy computation, the singleton functional fuzzy rules are adopted in many cases.

$$\begin{aligned} R^j &: If\ x_1\ is\ A_1^j\ and...and\ x_p\ is\ A_p^j \\ &Then\ y\ is\ c_0^j \end{aligned} \tag{3}$$

A fuzzy rule is a kind of logic implication, and this implication has two kinds of operations utilized in the most of applications: (i) Mamdani implication [15], or (ii) product implication [12] listed as follows.

$$\mu_{R_M}(x, y) = \min[\mu_A(x), \mu_B(x)], \tag{4}$$

or

$$\mu_{R_p}(x, y) = \mu_A(x) \cdot \mu_B(x). \tag{5}$$

Moreover, a fuzzy relation is defined as a subset of Cartesian product $X \times Y$, and hence a fuzzy relation is corresponding to a kind of fuzzy implication. In another word, a fuzzy rule is really a fuzzy relation. The kernel of a fuzzy system is the fuzzy inference engine [19] that can simulate the human thinking to reach a decision-making mechanism so as to solve the problem we encountered in the real world. The real operation for this inference could be written or described in the following simple example for understanding.

$$\begin{aligned} &premise\,1: x_1\, is\ A_1^{'}\ and\ x_2\ is\ A_2^{'}...and\ x_p\ is\ A_p^{'} \\ &premise\,2: If\ x_1\ is\ A_1\ and\ x_2\ is\ A_2...and\ x_p\ is\ A_p, Then\ y\ is\ B \\ &conclu\sin: y\ is\ B^{'} \end{aligned} \tag{6}$$

After this approximate reasoning, we obtain a fuzzy set output below.

$$\begin{aligned} B^{'} &= (A_1^{'} \wedge A_2^{'} \wedge ... \wedge A_p^{'}) \circ R \\ &= (A_1^{'} \wedge A_2^{'} \wedge ... \wedge A_p^{'}) \circ ((A_1 \wedge A_2 \wedge ... \wedge A_p) \to B) \end{aligned}, \tag{7}$$

If the max-min operation is used for the composition computation and Mamdanni implication is applied to this fuzzy relation in this rule, the effective formulation in the form of membership function for the above inference can be expressed as follows.

$$\begin{aligned} \mu_{B^{'}}(y) &= [\vee_{x_1}(\mu_{A_1^{'}}(x_1) \wedge \mu_{A_1}(x_1)] \wedge [\vee_{x_2}(\mu_{A_2^{'}}(x_2) \wedge \mu_{A_2}(x_2)] \wedge ... \\ &\quad \wedge [\vee_{x_p}(\mu_{A_p^{'}}(x_p) \wedge \mu_{A_p}(x_p)] \wedge \mu_B(y) \\ &= (\alpha_{A_!} \wedge \alpha_{A_2} \wedge ... \wedge \alpha_{A_p}) \wedge \mu_B(y) \\ &= \alpha \wedge \mu_B(y) \end{aligned} \tag{8}$$

$\alpha_{A_!}, \alpha_{A_2}, ..., and\ \alpha_{A_p}$ stand for the degree of compatibility between A_1 and $A_1^{'}$, A_2 and $A_2^{'}$,…, and A_p and $A_p^{'}$; α represented as the firing strength for the fuzzy rule. Supposing there are rules $R_j, j = 1,2,..., N$, the final output of a fuzzy inference engine could be formulated below.

$$\mu_{B^{'}}(y) = \mu_{B_1^{'}}(y) \vee \mu_{B_2^{'}}(y) \vee ... \vee \mu_{B_N^{'}}(y) , \tag{9}$$

The last part of the fuzzy system is defuzzifier that has six methods [19] provided in this part to defuzzify a fuzzy output into a crisp output.

(1-1)Center of gravity (continuous): $y^* = \frac{\int_U \mu_{B^{'}}(y)ydy}{\int_U \mu_{B^{'}}(y)dy}$ (10)

(1-2)Cnter of gravity (discrete): $y^* = \frac{\sum_{i=1}^{Q} \mu_{B^{'}}(y_i)y_i}{\sum_{i=1}^{Q} \mu_{B^{'}}(y_i)}$ (11)

(2)Mean of Maximum: $y^* = \frac{1}{M}\sum_{j=1}^{M} y_j$ (12)

(3)Modified mean of maximum: $y^* = \frac{\max_j y_j + \min_j y_j}{2}$ (13)

(4)Center average: $y^* = \frac{\sum_{j=1}^{N} \mu_{B_j^{'}}(\hat{y}_j)\hat{y}_j}{\sum_{j=1}^{N} \mu_{B_j^{'}}(\hat{y}_j)}$ (14)

(5)Modified center average: $y^* = \frac{\sum_{j=1}^{N} \mu_{B_j^{'}}(\hat{y}_j)\hat{y}_j \big/ \sigma_j\ X}{\sum_{j=1}^{N} \mu_{B_j^{'}}(\hat{y}_j) \big/ \sigma_j}$ (15)

(6)Weighted average: $y^* = \frac{\sum_{j=1}^{N} \alpha_j y_j}{\sum_{j=1}^{N} \alpha_j}$ (16)

The formula on Equation (16) just mentioned above provides a easy way for computing a crisp output from a specific fuzzy system and is usually used in many popular fuzzy applications. α_j, on Equation (16), represents the firing strength on jth fuzzy rule, and y_j stands for a fuzzy singleton output on the same fuzzy rule as α_j. This study would like to apply this fuzzy system to compute the weights of each item on affective instruction evaluation by taking the appraisal coefficients as the crisp input for the fuzzy system.

4. Verification and Discussion

The adopted currently available questionnaire for evaluating the affective instruction at most institutes has contained some certain items for Section I: student self-evaluation as well as Section II: evaluation of the instructor's teaching utilized for examining a list in a single sheet providing for students to evaluate it conveniently [8]. There is an example sampled from a certain institute in Taiwan concerning the affective instruction for Section I: student self-evaluation as well as Section II: evaluation of the instructor's teaching, totally containing 20 items as shown below.

Table 1

(a) Section I: Student self-evaluation

No.	Variables	Items
1	x_1	I am concentrated on lecturing during the class
2	x_2	I review lesson right away after class
3	x_3	I do my own homework or refer to peer's work partially
4	x_4	Interest in the course
5	x_5	Teaching hours of this course
6	x_6	Comparison with other course, hours I spend in this course
7	x_7	Attendances
8	x_8	Textbook used for the course
9	x_9	Instructor's requirements for students' academic performance
10	x_{10}	Predict your score of this course

(b) Section II: Evaluation of the instructor's teaching

No.	Variables	Items
1	y_1	Instructor's teaching content
2	y_2	Instructor's teaching methods
3	y_3	Instructor's text preparation
4	y_4	Instructor's expression
5	y_5	Instructor's teaching schedule
6	y_6	Instructor's abilities to enlighten students' creative thinking and answer tough questions
7	y_7	Instructor's enthusiasm to counsel students' academic task after class
8	y_8	Instructor's evaluation methods
9	y_9	Degrees of getting benefit from learning this subject
10	y_{10}	Instructor's general teaching effect

The evaluation in this questionnaire contains 20 items (variables) and every item can be graded from 1 to 7 by integer. Every student completed his individual evaluation with respect to a lecture in a classroom, and then every individual evaluation done by students in this classroom was brought to a procedure that is a cumulative statistic process. This process turned out to be a list in one sheet in which the average value of each item for each section was obtained. Every evaluated list represented the result of affective instruction evaluation in a lecture (sample). This experimental work was operated in 1200 samples (lectures) for 6 semesters [8] to get the average value for each item per semester as listed in Table 2.

Table 2

(a) The evaluated grades for student self-evaluation in average from item x_1 to item x_{10} for 6 semesters

Variables for 10 items	Semester #1	Semester #2	Semester #3	Semester #4	Semester #5	Semester #6	Average for 6 semesters
x_1	5.01	4.83	4.42	4.39	4.49	4.92	4.68
x_2	3.72	3.52	3.10	3.29	3.38	3.34	3.39
x_3	4.94	4.52	4.25	3.90	4.42	4.06	4.35
x_4	4.79	4.54	4.28	4.21	4.44	4.30	4.43
x_5	4.22	4.03	4.21	3.81	4.25	3.74	4.04
x_6	4.16	3.95	3.53	3.63	3.94	4.11	3.89
x_7	6.71	6.36	6.15	5.78	6.30	6.53	6.31
x_8	4.64	4.81	4.37	4.22	4.70	4.81	4.59
x_9	4.52	4.67	4.19	3.91	4.47	4.66	4.40
x_{10}	4.27	4.39	4.10	4.07	4.19	4.29	4.22

(b) The evaluated grades for evaluation of the instructor's teaching in average from item y_1 to item y_{10} for 6 semesters

Variables for 10 items	Semester #1	Semester #2	Semester #3	Semester #4	Semester #5	Semester #6	Average for 6 semesters
y_1	4.83	4.75	4.77	4.88	4.81	4.78	4.86
y_2	4.73	4.73	4.75	4.83	4.81	4.77	4.83
y_3	4.88	4.82	4.85	4.93	4.82	4.84	4.91
y_4	4.76	4.77	4.78	4.92	4.80	4.74	4.84
y_5	4.70	4.72	4.76	4.84	4.71	4.76	4.81
y_6	4.91	4.76	4.83	4.95	4.77	4.86	4.90
y_7	4.94	4.74	4.89	4.94	4.84	4.92	4.94
y_8	4.77	4.63	4.90	4.90	4.77	4.86	4.87
y_9	4.69	4.67	4.79	4.81	4.68	4.86	4.77
y_{10}	4.84	4.76	4.87	4.91	4.80	4.82	4.89

For this example cited in this paper, three grey numbers indicated as "Best Fitting", "Fitting", and "Worst Fitting" are represented as three grey whiten functions for appraisal displayed in the following Figure 3.

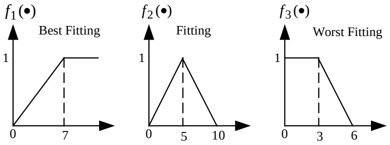

Figure 3

Three grey whiten functions for three grey numbers, "Best Fitting", "Fitting", and "Worst Fitting", respectively, are shown above as the appraisal functions.

After computation through the grey statistics method, a appraisal list with the appraisal coefficients for two separate sections for 6 semesters was asserted. According to the appraisal coefficients listed in Table 3, some of discussion could be made as follows:

Four appraisal coefficients, indicated as n_{23}, n_{53}, n_{63}, and n_{103} in Table 3- (a) as well as n_{33}, n_{43}, n_{53}, and n_{93} in Table 3- (b), could be viewed as the redundant items because their values of the appraisal coefficient for grey number "Worst Fitting" were great than 3.5 in Table 3- (a) as well as 2.4 in Table 3- (b) if these two separate values 3.5 and 2.4 are set by an appropriate manner (rule) that the number of trimmed items can not exceed over half of the number of the original items for each section as mentioned in the precede paragraph. Therefore, the restriction was defined to view the values of appraisal coefficients 3.5 in Table 3-(a) as well as 2.4 in Table 3-(b) as a threshold so that the items with the values of appraisal coefficients higher than a threshold could consider these correspond items to be a redundant item.

The group of grey number "Fitting" has the highest values in their appraisal coefficient among three group ("Best Fitting", "Fitting", and "Worst Fitting"); therefore, a conclusion was stated that the items for Section I: student self-evaluation as well as Section II: evaluation of the instructor's teaching were classified to the level of "Fitting" category.

Three appraisal coefficients, denoted by n_{11} and n_{71} in Table 3-(a) as well as n_{71}, n_{31}, n_{61}, and n_{71} in Table 3-(b), might be considered as the more significant items due to the higher values in the appraisal coefficient of grey number "Best Fitting" if a condition was set that the value of appraisal coefficient in grey number "Best Fitting" bigger than 4.0 in Table 3-(a) as well as 4.15 in Table 3-(b) as a level for classifying these items to be the significant ones. Two separate threshold values 4.0 and 4.15 are set in a manner to be similar to discussion #1 so that the number of significant items have to less than half of the number of the original items for each section as mentioned in the precede paragraph.

Table 3

A grey statistics applied for (a) Section I: student self-evaluation and (b) Section II: evaluation of the instructor's teaching to discover the redundant items by checking appraisal coefficients created by 3 grey whiten functions.

(a) Appraisal coefficients for Section I: student self-evaluation.

Appraisal Coefficient	$\sum_i f_1(\bullet)\cdot N_i$	Appraisal Coefficient	$\sum_i f_2(\bullet)\cdot N_i$	Appraisal Coefficient	$\sum_i f_3(\bullet)\cdot N_i$
n_{11}	**4.008**	n_{12}	5.608	n_{13}	2.647
n_{21}	2.907	n_{22}	4.070	n_{33}	**5.217**
n_{31}	3.662	n_{32}	5.218	n_{33}	3.303
n_{41}	3.705	n_{42}	5.312	n_{43}	3.147
n_{51}	3.953	n_{52}	4.852	n_{53}	**3.913**
n_{61}	3.331	n_{62}	4.664	n_{63}	**4.226**
n_{71}	**5.406**	n_{72}	4.434	n_{73}	0.073
n_{81}	3.953	n_{82}	5.510	n_{83}	2.816
n_{91}	3.776	n_{92}	5.284	n_{93}	3.193
n_{101}	3.616	n_{102}	5.062	n_{103}	**3.503**

(b) Appraisal coefficients for Section II: evaluation of the instructor’s teaching.

Appraisal Coefficient	$\sum_i f_1(\bullet)\cdot N_i$	Appraisal Coefficient	$\sum_i f_2(\bullet)\cdot N_i$	Appraisal Coefficient	$\sum_i f_3(\bullet)\cdot N_i$
n_{11}	4.117	n_{12}	5.764	n_{13}	2.394
n_{21}	4.089	n_{22}	5.724	n_{33}	**2.460**
n_{31}	**4.163**	n_{32}	5.828	n_{33}	2.286
n_{41}	4.110	n_{42}	5.754	n_{43}	**2.410**
n_{51}	4.069	n_{52}	5.698	n_{53}	**2.503**
n_{61}	**4.153**	n_{62}	5.820	n_{63}	2.306
n_{71}	**4.182**	n_{72}	5.854	n_{73}	2.243
n_{81}	4.117	n_{82}	5.766	n_{83}	2.391
n_{91}	4.071	n_{92}	5.700	n_{93}	**2.500**
n_{101}	4.143	n_{102}	5.800	n_{103}	2.333

Regard to the weights of items for two separate sections, applying the fuzzy inference mechanism for those the appraisal coefficients n_{i1} and n_{i3} , $i = 1,2,...,10$ could determine the weights of each items of affective instruction evaluation. First, the fuzzy rule base has to be constructed in an appropriate manner based on the idea that a large value for linguistic variable n_{i1} (“Best Fitting”) gets a higher weighted value, and thus a large value for linguistic variable n_{i3} (“Worst Fitting”) assigns a lower weighted value. A linguistic variable λ is defined as the relative weight to be a singleton fuzzy output of this fuzzy inference. Two fuzzy rules hence are set in the following IF-THEN statements.

$$\text{IF } n_{i1}=\text{Large and } n_{i3}=\text{Small THEN } \lambda=\text{High} \qquad (17)$$

$$\text{IF } n_{i1}=\text{Small and } n_{i3}=\text{Large THEN } \lambda=\text{Zero} \qquad (18)$$

Therefore, a fuzzy rule base with effectiveness and simplification for this study is shown in Table 4. Furthermore, the mark “×” as shown in Table 4 means that the rule doesn’t significantly contributed to the weight determination in this case; thus, it can be ignored or undefined.

Table 4

The fuzzy rule base contains two rules listed below for finding weights during the inference phase.

n_{i1} n_{i3}	**S**	**L**
S	×	**H**
L	**Z**	×

Note: **L**: Large, **S**: Small, **H**: High, **Z**: Zero, and × :Undefined

Next, the term set for respective linguistic variable is determined according to the domain (universal discourse) of every linguistic variable and an appropriate fuzzy number assignment as shown in Figure 4.

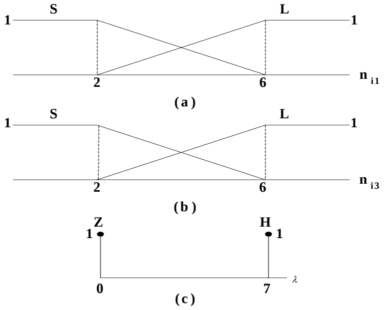

Figure 4

Three linguistic variables, n_{i1} “Best Fitting”, n_{i3} “Worst Fitting”, and λ ”Relative Weight” are defined as term sets {Large, Small}, {Large, Small}, and {High, Zero} respectively, as shown in (a), (b), and (c) above.

Third, computing the relative weight of each item of affective instruction evaluation could be done through means of the fuzzy inference. The weighted average method is applied in this defuzzification.

$$\lambda^* = \frac{\sum_{j=1}^{2}\alpha_j\lambda_j}{\sum_{j=1}^{2}\alpha_j} \qquad (19)$$

Finally, the weights for each item are accomplished in the way of proportional calculation as follows.

$$\omega_i = \frac{\lambda_i^*}{\sum_{j=1}^{10}\lambda_j^*} \qquad (20)$$

The results, before and after eliminating the redundant items, for evaluating the weights of items for two separate sections were listed in the Table 5 and 6, respectively. Four items were eliminated, and an important concept also was explained that (i) x_2 was merged to x_3, x_5 was merged to x_7, x_6 was merged to x_7, and x_{10} was merged to x_9. as shown in Table 6-(a) and (ii) y_2 was merged to y_1, y_4 was merged to y_6, y_5 was merged to y_7, and y_9 was merged to y_{10} as shown in Table 6-(b). Therefore, the original 10 items were reduced to a concise set with 6 items. The left items were x_1, x_3, x_6, x_7, x_8, and x_{10} for further examining their weights among 6 items.

Table 5

The weights (ω_i) for (a) Section I: student self-evaluation and (b) Section II: evaluation of the instructor’s teaching before eliminating the redundant items.

(a) Weights of items from item x_1 to item x_{10} for Section I: student self-evaluation.

No.	Variables for 10 items	Weight ω_i
1	x_1	0.130
2	x_2	0.035
3	x_3	0.097
4	x_4	0.103
5	x_5	0.087
6	x_6	0.064
7	x_7	0.172
8	x_8	0.121
9	x_9	0.103
10	x_{10}	0.088

(b) Weights of items from item y_1 to item y_{10} for Section II: evaluation of the instructor’s teaching.

No.	Variables for 10 items	Weight ω_i
1	y_1	0.099
2	y_2	0.097
3	y_3	0.104
4	y_4	0.099
5	y_5	0.095
6	y_6	0.103
7	y_7	0.106
8	y_8	0.100
9	y_9	0.095

Table 6

The weights (ω_i) for (a) Section I: student self-evaluation as well as (b) Section II: evaluation of the instructor’s teaching after eliminating the redundant items.

(a) Weights of items for Section I: student self-evaluation.

No.	Variables for 10 items	Weight ω_i
1	x_1	0.179
2	x_2	×
3	x_3	0.133
4	x_4	0.142
5	x_5	×
6	x_6	×
7	x_7	0.237
8	x_8	0.167
9	x_9	0.142
10	x_{10}	×

(b)Weights of items for Section II: evaluation of the instructor’s teaching.

No.	Variables for 10 items	Weight ω_i
1	y_1	0.162
2	y_2	×
3	y_3	0.169
4	y_4	×
5	y_5	×
6	y_6	0.168
7	y_7	0.173
8	y_8	0.162
9	y_9	×
10	y_{10}	0.166

5. Conclusions

The main purpose of this study is for acquiring effective items and determining their weights for affective instruction evaluation on engineering education, and this study has the following properties:

1. The introduced method in this study can extract the redundant items for (a) Section I: student self-evaluation as well as (b) Section II: evaluation of the instructor’s teaching by utilized the grey statistics method.
2. Applying the fuzzy inference mechanism could determine the weights of items for affective instruction evaluation on engineering education
3. After eliminating the redundant items and determining the weights of items on two separate sections, the affective instruction evaluation becomes a concise set for items with highly efficiency and reliability.

This is show that the grey statistics method followed by the fuzzy inference can reach a set of items with various weights rather than identical weights and the number of items reduced so as to retain the significant ones with higher availability for evaluation of instructor’s teaching in the affective instruction evaluation. This study just proposed one of methods for acquiring effective items and determining their weights for affective instruction evaluation on engineering education, but there is probably another alternative to resolve the same issue discussed in this study.

6. References

[1] B. S. Bloom, D. R. Krathwohl, and B.A. Masia, *Taxonomy of Educational Objectives, Handbook I: Cognitive Domain*, David Mckay Co., N. Y., 1984.

[2] B. S. Bloom, D. R. Krathwohl, and B.A. Masia, Taxonomy of Educational Objectives, Handbook II: Affective Domain, David Mckay Co., N. Y., 1984.

[3] I. E. Sonnier, *Affective Education: Methods and Technique*, Englewood Cliffs, NJ: Educational Technology Publications, 1989.

[4] Tom Kubiszyn, and Gary Borich, *Educational Testing and Measurement, 5th Edition*, HarperCollins College Publishers, 1997.

[5] N. E. Gronlund, and R. L. Linn, *Measurement and Evaluation in Teaching, 6th ed.*, Macmillan, New York, 1990.

[6] M. Q. Patton, *How to Use Qualitative Methods in Evaluation*, Sage Publication, London, 1987.

[7] Department of Technological & Vocational Education, A Manual for Teachers Instruction Evaluation in the Junior College, Ministry of Education Press, Taiwan, 1989.

[8] B. R. Chang, Analysis of Multivariate Affective Instruction Evaluation on Engineering Instruction, *Proc. International Conference on Engineering Education 2000*, Grand Hotel, Taipei, Taiwan, August 14-16, 2000. (Accepted Paper ID: TuA8-4).

[9] J. L. Deng, *A Course on Grey System Theory*, Huazhong University of Science & Technology Press, Wuhan, 1990.

[10] J. L. Deng, *The Essential Methods of Grey Systems*, Huazhong University of Science & Technology Press, Wuhan, 1992.

[11] H. J. Zimmermann, Fuzzy Set Theory and Its Application, Kuuwer-Nijhoff, M. A., 1985.

[12] G. J. Klir, and B. Yuan, Fuzzy Sets and Fuzzy Logic, Theory and Applications, Prentice-Hall, N.J.,1995.

[13] C. T. Lin, and C. S. George Lee, Neural Fuzzy System: A Neuro-Fuzzy Synergism to Intelligent Systems, Prentice-Hall, N. J., 1996.

[14] J. S. R. Jang, C. T. Sun, and E. Mizutani, Neuro-Fuzzy nd Soft computing, Prentice –Hall, N. J., 1997.

[15] E. H. Mamdani and S. Assilian, “An Experiment in Linguistic Sythesis with a Fuzzy Logic Controller,” Int. J. Of Man-Machine Studies, vol. 7, no. 1, pp. 1-13,1975.

[16] T. Takagi and Sugeon, “Fuzzy identification of System and Its Applications to Modeling and Control,” IEEE Trans. On System, Man, and Cybernetics, vol. 15, no. 1, pp. 116-132, 1985.

[17] M. Sugeon and G. T. Kang, ”Structure Identification of Fuzzy Model,” Fuzzy Sets and Systems, vol. 28, pp. 15-33, 1988

[18] Y. Tsukamoto, “ An Approach to Fuzzy Reasoning,” in Madan M. Gupta, Rammohaw K. Ragade, and Ronald R. Yager, editors, Advances in Fuzzy Set Theory and Applications, pp. 137-149, North-Holland, Amerterdam, 1979

[19] .B. Kosko, Neural Networks and Fuzzy System, Prentice-Hall, N. J. , 1992.