Multi-Criteria Decision-Making for Evaluation of Student Academic Performance Based on Objective Weights

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***Abstract*—Student academic evaluation is part of the learning process in order to control the student's learning progress. The evaluation will show whether the student will pass or fail and for an instructor to guide for future evaluations on performance. There are criteria such as student's gender, student's age when they are registered in university, student's 1st semester GPA, etc., which exist in academic data can be utilized to get the student academic performance using multi-criteria decision making. Multi-Objective Optimization by Ratio Analysis (MOORA) and Simple Multi-Attribute Rating (SMART) was two simple technique in multi-criteria decision making that the criteria weight can be determined objectively using entropy and gain values. This paper tries to evaluate the student academic performance using MOORA and SMART with criteria weight and sub-criteria weight resulted from entropy and gain. Decision output out of MOORA and SMART then compared with actual data using confusion matrix to discover the performance of those criteria and sub-criteria weight. The result showed that the performance of criteria weight with accuracy was 60.9 percent and the criteria of fourth-grade point average have the biggest impact on student academic evaluation with 0.1589 of weight. The result of this research can be used to help the instructor to determine the weight of student criteria for future recommendations and evaluations on student performance.**

Keywords— student, academic, evaluation, entropy, MOORA, SMART

I. INTRODUCTION

Student academic evaluation is part of the learning process in order to control student learning progress. Learning process evaluation is a process to determine an academic performance level of the student which comprehensive and continuous in accordance with the educational regulation. The evaluation will show whether the student will pass or fail and for an instructor to guide for future evaluations on performance [1].

An in-depth study of student's degree-completion time, the degree-completion time is influenced by eleven (11) criteria. There are student's gender, student's age when they are registered in university, student's place of birth, student's high school major, student's high school basic funding source, student's 1st semester GPA, student's 2nd semester GPA, student's 3rd semester GPA, student's 4th semester GPA, student's participation in non-academic organization, and student's degree-completion time [2].

The number of influential criteria encourages the use of computer systems to process data in a decision is called a decision support system. Decision support systems that use multiple criteria are called multi-criteria decision support systems (MCDM). MCDM is used to establish the best alternative of a number of alternatives based on certain criteria [3].

Multi-Objective Optimization by Ratio Analysis (MOORA) is one of the multiple criteria decision-making techniques especially in terms of reference point technique [4]. MOORA is the process of simultaneously optimizing two or more conflicting attributes subject to certain constraints [5]. Among these conflicting criteria, some of them have beneficial nature where maximum values are desired and non-beneficial nature criteria for ranking alternatives from a set of available feasible options [6].

Simple Multi-Attribute Rating (SMART) is a comprehensive model of decision-makers to account for the thing that is qualitative or quantitative and supporting the simplest decision [7]. SMART is proposed on the theory that each alternative consists of some criteria that have values and each criterion have weights that describe how important compared to other criteria [8].

Furthermore, the criteria weight in MOORA and SMART can be determined subjectively by decision maker or objectively using entropy and gain values. The utilization of entropy method in determining objective criteria weights is relied upon the measurement of uncertain information contained in the decision matrix which directly creates a set of weights for a given criterion based on the mutual contrast of individual criteria values of variants for each criterion and then for all the criteria at simultaneous [9]. Entropy is the amount of information indicating the size of impurities. The impurity measure can determine how informative an attribute input is in the form of sub-criteria. Furthermore, this research uses the entropy value of each sub criteria as the weight of the sub-criteria. While the gain is the result of the attribute selected using entropy to determine the best attribute. The greater the gain of criteria the is, the more influential the criteria becomes [10].

Therefore this study will analyze the performance of the weight resulted using MOORA and SMART method and calculate out of it with confusion matrix. The purpose of this research is to help the instructor to determine the weight of student criteria for future recommendations and evaluations on student performance.

II. Related Works

Implementation MOORA method for parametric optimization of milling process resulted that as this method is based only on simple ration analysis, it involves the least amount of mathematical calculations, which may be quite useful and helpful to the decision makers who may not have a strong background in mathematics [5].

In other research of GMAW (current, voltage and torch angle) process parameters in stainless steel cladding, it has been noticed that the MOORA method has effectively optimized [11].

Based on the result of the research of simple multi-attribute rating technique (SMART) for decision support conducted with number of dynamic alternatives and use three criteria then the process of calculation using the SMART method does not require a long time, but different if the alternatively added dynamically with the number of constant alternatives then the process of calculating the SMART method will require process time which is longer [8].

From the previous research, MOORA has simple in the mathematical calculation but still effectively optimized. Then, SMART has the fast process of calculation. So, this study will analyze the performance of weight resulted using MOORA and SMART. The results of this study will point out the performance of objective weight resulted from entropy and gain.

III. Criteria's Weight Performance Analysis Process

A. Alternative Dataset

In this paper, alternatives dataset is generated from graduate's data of time required to complete study in *Faculty of Computer Science and Information Technology* (FKTI), *Mulawarman University* (Unmul) from July 2015 to December 2017. This dataset used to implement entropy weights into the MOORA and SMART method in the process of ranking student academic performance.

B. Objective Weight Process

To determine the criteria weights used Entropy and gain value. Entropy is the amount of information indicating the size of impurities. The impurity measure can determine how informative an attribute input is in the form of sub-criteria. Furthermore, this research uses the entropy value of each sub-criteria as the weight of the sub-criteria. While the gain is the result of the attribute selected using entropy to determine the best attribute. The greater the gain of criteria is, the more influence this criterion has [10].

The following equation (1) shows us how to get entropy value and equation (2) shows us gain value:

$$Entropy(S) = \sum_{i=1}^{n} -pi * log_2\, pi \quad (1)$$

In equation (1), S means the set of the cases, n is a count of S partition, and pi is Si to S proportion. For example, in SMA of high school major, there are 66, 58, 169 for Si $(i = 1,2,3)$ and 293 for S.

$$Gain(S, A) = Entropy(S) - \sum_{i=1}^{n} \left|\frac{S_i}{S}\right| * Entropy(S_i) \quad (2)$$

In equation (2), S denotes the set of the cases, A is an attribute, n is an amount of attribute partition A, $|Si|$ is a number of cases in the i partition, and $|S|$ is an amount of S cases. For example, in the high school major, there are 1414 of entropy S reduced by summing 293 and 157 of S_i $(i = 1,2,3)$ by the 450 and multiplying with entropy S_i.

The TABLE I presents the criteria weighting and sub-criteria weighting obtained from the possibility of gain for criteria and entropy for sub-criteria for each student's sub-criteria and criteria.

TABLE I. Crteria's Weight and Sub-Criteria's Weight

Criteria	Value	Sum	F	M	S	Entropy	G
Sum		450	95	98	257	1.414	
Gender							0.023
	Male	314	51	70	193	1.34	
	Female	136	44	28	64	1.508	
Age							0.022
	<18 years old	68	8	10	50	1.096	
	18 years old	274	68	56	150	1.443	
	>18 years old	108	19	32	57	1.448	
Place birth							0.002
	University place	159	34	39	86	1.453	
	Non-university place	291	61	59	171	1.39	
High school major							0.004
	SMA	293	66	58	169	1.405	
	SMK	157	29	40	88	1.421	
High school funding							0.006
	State	388	81	79	228	1.39	
	Private	62	14	19	29	1.52	
1st GPA							0.035
	1.6-2.59	17	2	2	13	1.022	
	2.6-3.59	318	58	61	199	1.328	
	3.6-4	115	35	35	45	1.574	
2nd GPA							0.136
	0.0-1.59	6	0	0	6	0	
	1.6-2.59	31	2	0	29	0	

Criteria	Value	Sum	F	M	S	Entropy	G
	2.6-3.59	270	39	59	172	1.297	
	3.6-4	143	54	39	50	1.572	
3rd GPA							0.07
	0.0-1.59	1	0	0	1	0	
	1.6-2.59	19	1	0	18	0	
	2.6-3.59	335	60	72	203	1.359	
	3.6-4	95	34	26	35	1.573	
4th GPA							0.159
	0.0-1.59	19	0	0	19	0	
	1.6-2.59	17	0	0	17	0	
	2.6-3.59	192	25	27	140	1.113	
	3.6-4	222	70	71	81	1.582	
Organization							0.008
	Join	31	8	11	12	1.565	
	Non-join	419	87	87	245	1.394	

Below is detailed description from Table I:

F : fast to complete study in less than four years
M : moderate to complete study in four years
S : slow to complete study in more than four years
G : gain value for each criterion

The equation (1) is entropy formula is, used to generate the weight of each sub-criterion. The weight of each criterion generated by the gain formula is shown on equation (2). Figure 1 is the value of entropy weight in table 1 that present the rank bar of weighted criteria and weighted sub-criteria determined by the chance of gain for criteria and entropy for sub-criteria.

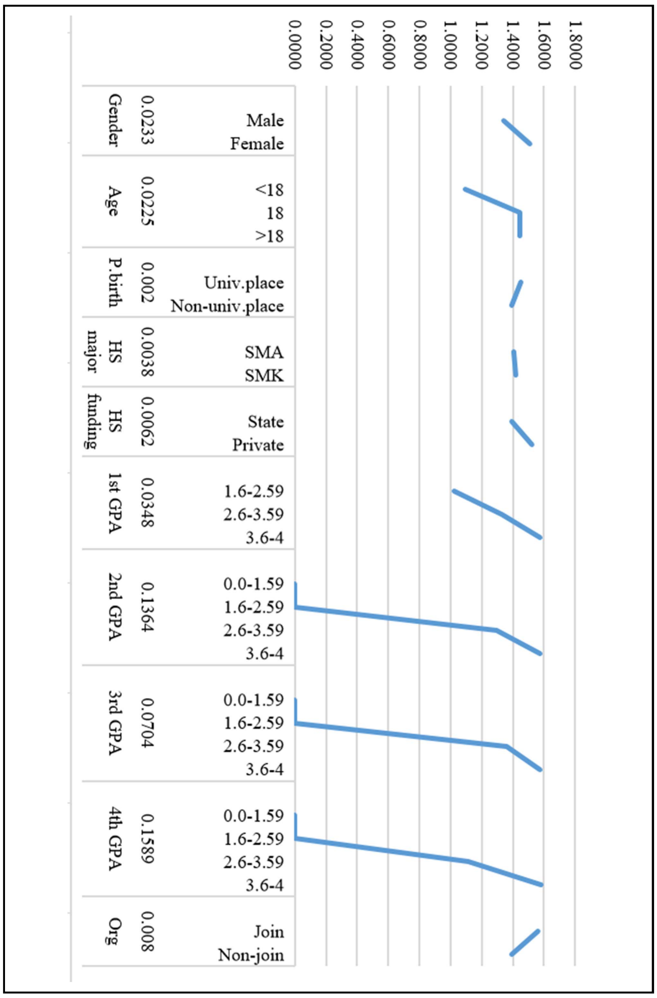

Fig. 1. Entropy Weight Result of Student Criteria

Figure 1 shows the comparison of each sub-criterion influence in regard to how fast students complete their study. In figure 1, it is shown that the criteria of the 4th GPA and sub-criteria 3.6 to 4 have the most influence on student academic evaluation.

C. *Multi-Objective Optimization by Ratio Analysis (MOORA) Process*

The first step is to determine the objective and to identify the pertinent evaluation attributes. The next step is to represent all the information available for attributes in the form of the decision matrix. The basic logic of simple additive weighting is to obtain a weighted sum of the performance ratings of each alternative overall attributes. Then a ratio system is developed in which each performance of an alternative on the attribute is compared to a denominator which is a representative for all the alternatives concerning that attribute. This matrix available in the form of normalizing decision matrix. For this the ratio can be expressed by the square root of the sum of squares of each alternative per attribute by equation (3):

$$X*_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \quad (3)$$

where i=1,2,3,…,n.

For MOORA, these normalized performances are added in case of maximization (for beneficial attributes) and subtracted in case of minimization (for non-beneficial attributes). In order to give more importance to an attribute, it could be multiplied by its corresponding weight. In this paper, the weight used is gain value for each criterion. Then the optimization problem is obtained by equation (4):

$$y_i = \sum_{j=1}^{g} W_j X *_{ij} - \sum_{j=g+1}^{n} W_j X *_{ij} \quad (4)$$

where i=1,2,3,…,n.

The y_i value can be positive or negative depending on the totals of its maxima (beneficial attributes) and minima (non-beneficial attributes) in the decision matrix. An ordinal ranking of y_i shows the final preference. Thus, the best alternative has the highest y_i value, while the worst alternative has the lowest y_i value [5]. The result of MOORA preference value shown in TABLE II

TABLE II. PREFERENCE VALUE OF MOORA

No	Student Number	Preference Value
1	1415015xxx	0.02269187
2	1415015 xxx	0.02272525
3	1415015 xxx	0.02521697
4	1215015 xxx	0.02414518
5	1115015 xxx	0.02056255
6	1115015 xxx	0.02191676
7	1115015 xxx	0.02217795
8	1115015 xxx	0.01994223
9	1115015 xxx	0.02337577
10	1115015 xxx	0.02505513
⋮		
450	1007055 xxx	0.00465983

D. Simple Multi Attribute Rating (SMART) Process

The first step of the SMART method determines the number of criteria used. In this paper, the number of criteria is the gain value of each criterion. Second, determine the sub-criteria by using the 1-100 interval using equation (5):

$$= \frac{w_j}{\sum w_j} \quad (5)$$

Where Wj is the weight of value, while $\sum W_j$ is the total weight of all criteria. Third, provide criteria parameter value on each criterion for each alternative. Then determine the value of the utility to convert the value of the criteria for each criterion into the value the raw data criteria [7]. Utility value is obtained using equation (6):

$$u_i(a_i) = 100 \frac{c_{max} - c_{out\, i}}{c_{max} - c_{min}} \% \quad (6)$$

Determining the final value of each criterion by shifting the values obtained from the normalized value of the raw data criteria with weight normalized value criteria. Below is the preference $U(a_i)$ given as the following equation (7):

$$U(a_i) = \sum_{j=1}^{m} W_j . u_i(a_i) \quad (7)$$

The lower the value $U(a_i)$ is, the more preferred the alternative. The result of SMART preference value is shown in the following TABLE III:

TABLE III. PREFERENCE VALUE OF SMART

No	Student Number	Preference Value
1	1415015xxx	6.695390279
2	1415015 xxx	5.50442902
3	1415015 xxx	4.148344904
4	1215015 xxx	8.705073845
5	1115015 xxx	11.59278633
6	1115015 xxx	8.04692743
7	1115015 xxx	7.652588545
8	1115015 xxx	12.62306506
9	1115015 xxx	7.689600177
10	1115015 xxx	3.374929156
⋮		
450	1007055 xxx	42.47204624

E. Confusion Matrix Process

To measure the performance of the MOORA and SMART methods by using entropy weights to ranking alternatives as a result of the evaluation of students' academic performance using a confusion matrix. Alternative ranking describes the higher the alternative weight, the better the student's academic performance and the time to complete the study will be faster.

The confusion matrix is obtained by calculating the accuracy, sensitivity and specificity measures. The matrix present classified samples as true, while others as false and misclassified. In this paper, the accuracy and the precision of MOORA and SMART are calculated by using the confusion matrix. The dataset used as a standard is real degree-completion time for the graduate student. Below is the accuracy by equation (8):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

TP is true positive, TN is the true negative, FP is false positive, and FN is the false negative. For the positive predictive value or precision formula are given as the equation below:

$$PPV = \frac{TP}{TP+FP} \quad (9)$$

In equation (9) PPV is positive predictive value. In this paper, there are three classes of degree-completion time namely fast, moderate, and slow. Hence the precision of each method is the average precision of each class.

Based on the academic dataset, there are 95 students are fast graduated, 98 students are the moderate graduate, and 257 students are the slow graduate from 450 data of student degree-completion. The preference value in TABLE II, III, and IV are formed into three categories as fast, moderate, and slow. Each category is compared with the actual data of degree-completion time from graduate's data. The result of the comparison of both method, MOORA and SMART, is presented in the confusion matrix below:

TABLE IV. CONFUSION MATRIX OF MOORA

		MOORA		
		Fast	Moderate	Slow
Real	Fast	40	25	29
	Moderate	23	41	35
	Slow	32	32	193

TABLE V. CONFUSION MATRIX OF SMART

		SMART		
		Fast	Moderate	Slow
Real	Fast	41	27	27
	Moderate	24	38	35
	Slow	30	33	195

The comparison result in table IV shows that there are 40 actual data from 95 data in the fast category and it has high MOORA's alternative preference. It indicates there are 40 data that are related to the actual data for fast categories. Likewise, for other categories, there are 41 data in the medium category and 193 data in the slow category that corresponds to the results of the moora ranking with the actual data. Using equation (8) and (9), the accuracy result of MOORA is 0.608888889 or 60.9% and the precision is 0.530130914 or 53.01%. From the comparison result in table V and calculation using equation (8) and (9), the accuracy result of SMART is 0.608888889 or 60.9% and the precision is 0.526029638 or 52.7%. The accuracy and precision rate of the methods are shown in figure 2.

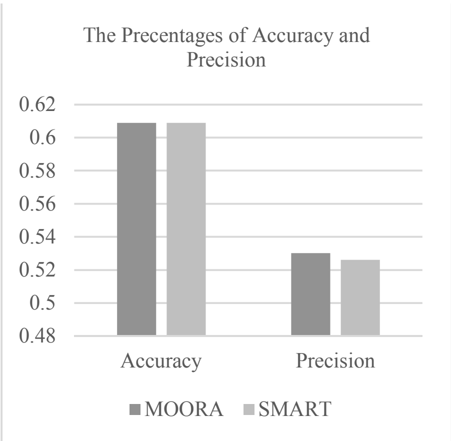

Fig. 2. Bar Chart of The Percentage of Accuracy and Precision

Figure 2 shows that MOORA and SMART accuracy has exactly the same percentages but MOORA has higher precision percentages. So, the performance of weight resulted by entropy and weight has percentages of accuracy with 60.9% and precision between 52.7% to 53.01%.

IV. CONCLUSION

From the work result and discussion, it can be concluded that the weighting of ten criteria using entropy shows us some interesting criteria having the biggest impact on the student academic performance evaluation. There are grade point average, student's gender, and age when they registered. Also, the performance of student criteria's weight can be calculated by multi-criteria decision making. Based on the result of criteria's weight performance analysis using MOORA and SMART preference in confusion matrix, the performance of weight has percentages of accuracy with 60.9% for MOORA and 60.9% for SMART, and precision between 52.7% to 53.01%. The result of this research can be used to help the instructor to guide for future recommendations and evaluations on performance when the similar criteria to this case study are available.

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