Novel Approach to Facilitating Tradeoff Multi-Objective Grouping Optimization

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Abstract—The grouping problem is critical in collaborative learning (CL) because of the complexity and difficulty in adequate grouping, based on various grouping criteria and numerous learners. Previous studies have paid attention to certain research questions, and the consideration for a number of learner characteristics has arisen. Such a multi-objective grouping problem is with conflicting grouping objectives, involving the benefit objective (e.g. learning achievement) and cost objective (e.g. class rank) which are conflicting in different directions. This study first proposed a novel approach based on the enhancement of a Genetic Algorithm (GA) with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for facilitating the tradeoff multi-objective grouping optimization, and based on the proposed approach further developed a web-based group support system to help educators for adequate grouping of homogeneous inter-group and heterogeneous intra-group. In addition, the distribution of learners in the class was considered for group formation. Two types of experiments were conducted; one involved a performance analysis against a GA and the Random approach, and the other entailed a study on CL with 90 participants. The experimental results showed the following: 1) The proposed approach is not only more effective than a GA and the Random approach but also more efficient than a GA. 2) As a grouping strategy, the proposed approach can facilitate improved learning performance with statistical significance; in other words, the developed system is able to adequately allocate learners to teams for facilitating CL.

Index Terms—Collaborative learning (CL), decision support, evolutionary computing, genetic algorithms (GAs), IT applications

1 Introduction

Collaborative learning (CL) has been defined as learning in a group through discussion and joint knowledge construction [1]. CL is consistent with the manner of knowledge construction proposed by Vygotsky [2], according to which learners acquire new knowledge and skills through teamwork [3]. CL has been successfully used in education as a pedagogic strategy to supplement and enrich individual learning [4] and improve academic performance [5]. Several studies have argued that with advanced computer technologies, computer-supported CL not only provides a superior experience but also promotes motivation and improves learning achievements [6], [7], [8].

In particular, considering that group formation is crucial in CL, dividing learners into groups has been widely regarded as essential [1], [9]. Khandaker and Soh [9] stated that inadequate grouping leads to failed collaboration. For example, random assignment and self-organized grouping traditionally have been employed by instructors to allocate learners into groups. However, random assignment and self-organized grouping lead to inadequate grouping, resulting in only certain groups achieving learning goals [10], [11], [12]. Consequently, as Moreno et al. [1] stated, adequate grouping, which considers various criteria for group formation, facilitates improved interaction and leads to superior learning results.

However, learning achievement is not the only grouping criterion. Liu and Tsai [13] suggested that adequate grouping does not depend on having members with high achievements. Moreover, various grouping criteria have been explored and shown to be related to learner status, such as knowledge level, communicative and leadership skills, interests, and learning styles [1], [11], [14], [15]. With increasing numbers of learners, it is difficult for instructors to consider multiple grouping criteria [14], [16]. Because the workload for instructors is generally high, and considering the need for fulfilling various grouping criteria [3], [17], the complexity of group formation for effective CL has been likened to solving an NP-hard problem [1], [3], [14].

Several studies have investigated the grouping problem in CL. Wang et al. [18] constructed a computer-supported grouping system based on a GA considering thinking style of learners. Kyprianidou et al. [15] developed a web-based grouping system concerning learning styles, and Liu et al. [11], [19] also considered learning styles in their proposed intelligent grouping. Ounnas et al. [20] presented a framework based on semantic web technology and logic programming, considering the involved constraints and avoiding the orphan problem. Chan et al. [21] used a GA considering group complementary scores. Hubscher [17] used a tabu search algorithm concerning context-specific preferences for project groups, and a new general criterion, called evenly skilled, was proposed. Lin et al. [14] enhanced particle swarm optimization to understand levels and interests, and Zheng and Pinkwart [22] presented a discrete

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particle swarm optimization considering MBTI (Myers-Briggs Type Indicator) personality and gender.

Khandaker and Soh [9] proposed iHUCOFS framework considering the balance of learner competence and compatibility. Based on their proposed multi-agents framework, they implemented the ClassroomWiki considering learning contribution [23]. Tan et al. [24] presented the location-based dynamic grouping for collaborative mobile learning; also, learners' learning profile, styles, and interests were considered. Huang and Wu [25] proposed an algorithm entailing a ubiquitous learning portfolio. Agustín-Blas et al. [26] presented a model based on the problem of Machine-Part Cell Formation, and proposed a hybrid GA to solve it. Yeoh and Nor [27] presented an algorithm considering gender and race. Yannibelli and Amandi [3] proposed a deterministic crowding GA concerning the learner's role based on Belbin's model [28], [29]. Srba and Bielikova [12] considered feedback from learners' collaborations for dynamic groups, because the learner characteristics did not complement each other in changing short-term groups.

Above studies have paid attention to certain research questions, and the consideration for a number of learner characteristics has been arisen. Such problem is difficult and interesting and has engaged researchers in studying. For examples, Hwang et al. [16] enhanced a GA to satisfy multiple grouping criteria, and Moreno et al. [1] further translated the grouping problem into multi-objective optimization by employing a GA. Consequently, the multi-objective grouping optimization has been a great importance in CL.

Each grouping criterion related to a learner's characteristic is defined as a benefit objective (the higher the more favorable) or a cost objective (the lower the more favorable). For example, learning achievement is a benefit objective because a higher learning achievement is more favorable; by contrast, class rank is a cost objective because a lower class rank is more favorable. Because the benefit and cost objectives conflict in opposite directions and both involve a tradeoff, the grouping problem considering multiple grouping criteria related to learner characteristics can be described as a tradeoff multi-objective grouping optimization. Previous methods involved translating the grouping criteria to the same direction, which increased not only the workload but also the probability of mistakes by the instructors. However, instructors must concentrate on pedagogical theories for designing CL activities.

In addition, based on educational theories of CL, the typical grouping strategies involve heterogeneous intra-group (dissimilar members) and homogeneous inter-group (similar groups), which are widely used in CL activities [3], [17], [22], [25]. A heterogeneous group is composed of several members whose gender, achievements, and skills etc., are different or complementary. In particular, the group members are assigned the levels of low, medium, and high, which are distributed in the class. A group is a microcosm of the class, in which the advanced learners help the learners in need. In addition, to make competition among the groups fairer, all groups must be balanced and homogeneous regarding the overall performance of each group. However, previous approaches have directed little attention toward the distribution of learners regarding group formation, and there is still a lack of feasible solutions. In addition, addressing the aforementioned multiple grouping criteria is time-consuming for achieving heterogeneous intra-group and homogeneous inter-group with a high number of learners, and increases the workload of instructors. Therefore, improving the quality of grouping solutions is difficult.

Hence, this study first proposed a novel approach for facilitating the tradeoff multi-objective grouping optimization. Further, a web-based group support system based on the proposed approach was developed to assist instructors in allocating learners to heterogeneous intra-group and homogeneous inter-group. Such a grouping solution not only prevents inadequate grouping resulting from random assignment and self-organized grouping, but also facilitates superior learning interaction within the group and among the groups. The proposed approach considers the scalability for multiple grouping criteria related to learner characteristics, which are defined as benefits and costs. The distribution of learners in the class is considered in group formation. To promote a higher quality of grouping solutions, the proposed approach is based on the enhancement of a Genetic Algorithm (GA) with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The developed system, which is easy to use, enables instructors to reduce their workload and the probability of mistakes; consequently, they have more time to concentrate on pedagogical theories for designing CL activities, thereby increasing the quality and efficiency of teaching.

2 Genetic Algorithm

The GA proposed by Holland [30] is population-based and employs swarm intelligence; it simulates evolutional theory to search the problem space in multiple parallels and identify possible alternatives. GAs have been widely studied in the context of e-learning, in applications such as autoreply accuracy optimization [31] and learning style identification [32]. In addition, GAs have been successfully used to approach solutions to NP-hard problems, for example the test sheets construction [33]. In this study, a GA was adopted because of previous relevant experiences of identifying near-optimal solutions to NP-hard problems with an acceptable computational effort.

3 Technique for Order Preference by Similarity to Ideal Solution

The TOPSIS, proposed by Hwang and Yoon [34], is a multiple criteria/objectives decision-making technique entailing certain alternatives that define a positive-ideal solution and a negative-ideal solution for each criterion. In addition, each criterion is defined as a benefit objective or a cost objective. The positive-ideal solutions maximize the benefit criteria and minimize the cost criteria, whereas the negative-ideal solutions maximize the cost criteria and minimize the benefit criteria. For alternative decision making, their orders of priority are based on a similarity to the ideal solution; in other words, the most favorable outcome is the nearest to the positive-ideal solutions and also the furthest from the negative-ideal solutions.

	L_1	L_2	L_3	L_4	L_5	L_6	L_7	
C_1	70	60	80	50	30	40	90	
C_2	60	70	90	40	30	50	80	X_{sq}
C_3	3	4	1	6	7	5	2	
C_1	0.67	0.50	0.83	0.33	0.00	0.17	1.00	
C_2	0.50	0.67	1.00	0.17	0.00	0.33	0.83	X'_{sq}
C_3	0.33	0.50	0.00	0.83	1.00	0.67	0.17	
D_s^+	0.39	0.46	0.09	0.79	1.00	0.72	0.14	
D_s^-	0.62	0.56	0.95	0.23	0.00	0.29	0.89	
Z_s	0.61	0.55	0.91	0.23	0.00	0.29	0.86	

Fig. 1. Matrix regarding *S* learners with *Q* grouping criteria.

The TOPSIS comprises four steps: Step 1. Constructing a decision-making matrix. This step involves constructing a matrix for considering multiple criteria regarding alternatives. The matrix is constructed by allocating the alternatives to the left of the matrix, allocating the criteria to the top of the matrix, and filling the cells <alternatives, criteria> of the matrix with the values of the criteria of the alternatives. Step 2. Determining a positive-ideal solution and a negative-ideal solution. This step entails determining a positive-ideal solution and a negative-ideal solution for each criterion based on whether the criteria represent a benefit or a cost objective. Step 3. Using the m-dimensional Euclidean distance to compute two measures. This step involves computing the Euclidean distance from the positive-ideal solutions for the criteria as one measure, and the Euclidean distance from the negative-ideal solutions for the criteria as an additional measure, for each alternative. Step 4. Computing the relative closeness to the ideal solution. This step entails computing the relative closeness to the ideal solution for each alternative, on the basis of considering the distance from the positive-ideal solutions of the criteria and distance from the negative-ideal solutions of the criteria. The most favorable alternative considering multiple criteria is that which is the nearest to the positive-ideal solutions and also the furthest from the negative-ideal solutions.

The TOPSIS has been successfully employed in various applications including multiple criteria/objectives decision-making in, for instance, patent rankings [35], project portfolio selection [36], and reverse logistics contractor selection [37]. Because the TOPSIS is effective in making decision for satisfying multiple criteria or objectives problems, it may be a suitable alternative for achieving tradeoff multiple grouping objectives.

4 Educational Scenario of Grouping Problem with Tradeoff Multi-Objective Grouping Optimization

A real-life learning scenario is described as follows. In the school, students are allocated to groups for CL. Teachers typically consider student characteristics for the grouping criteria, such as their learning behavior and style, degree of cooperation, personal preference, and communication. Each factor is quantified and given a value; in addition, each factor is defined as a benefit objective or a cost objective. For factors representing a benefit objective, a high value is favorable; by contrast, for factors representing a cost objective, a low value is favorable. For example, teachers consider the number of completed exercises, total score of completed exercises, total time to complete exercises, absence rate, total score of tests, and class rank for grouping. The number of completed exercises, total score of completed exercises, and total score of tests are defined as benefit objectives, because high values are more favorable than low ones. The total time to complete exercises, absence rate, and class rank are cost objectives, because low values are more favorable than high ones. Moreover, because the benefit and cost objectives conflict in opposite directions, several factors represent a tradeoff. For example, class rank represents a tradeoff in conjunction with the number of completed exercises, total score of completed exercises, and total score of tests.

Consequently, the aforementioned real learning scenario can be summarized as follows. The grouping problem is a tradeoff multi-objective grouping optimization in which a number of learners must be allocated to groups by considering multiple grouping criteria related to learner characteristics. In addition, the grouping criteria are defined as benefit objectives (i.e., the higher the more favorable) and cost objectives (i.e., the lower the more favorable) and are weighted. Assume the following representations: $\boldsymbol{L} = \{ L_s \}, 1 \leq s \leq S$, where S denotes the number of learners, s denotes the iteration of S, $\boldsymbol{L}$ denotes a set of S learners, and L_s denotes the sth learner in the set of learners. $\boldsymbol{G} = \{ G_t \}, 1 \leq t \leq T$, where T denotes the number of needed groups, t denotes the iteration of T, $\boldsymbol{G}$ denotes a set of T groups, and G_t denotes the tth group in $\boldsymbol{G}$. $\boldsymbol{C} = \{C_q\}, C_q \in \text{Benefit} \mid \text{Cost}, 1 \leq q \leq Q$, where Q denotes the number of grouping criteria, q denotes the iteration of Q, $\boldsymbol{C}$ denotes a set of Q grouping criteria, and C_q denotes the qth grouping criterion in $\boldsymbol{C}$; each grouping criterion is related to the learner's characteristic and defined as a benefit objective or a cost objective. $\boldsymbol{W} = \{ W_q \}$, where $\boldsymbol{W}$ denotes a set of Q weights, and W_q denotes the qth weight in $\boldsymbol{W}$; the weight is used for the importance of the qth grouping criterion. The grouping problem with tradeoff multi-objective grouping optimization searches a near-optimal solution for dividing S learners into T groups by considering Q weighted grouping criteria which represent benefit or cost objectives. Moreover, the grouping solution needs to satisfy the heterogeneous intra-group and homogeneous inter-group requirements to ensure superior learning interaction within the group and among the groups.

5 Novel Approach Based on Enhancement of Genetic Algorithm with TOPSIS

5.1 Preparation

First, the distribution of learners in the class is determined to form groups. Normal distribution is a general practice in a class where the levels of learners are categorized as low, medium, and high. The structures and sizes of groups are determined according to the distribution.

The S learners with Q grouping criteria are represented as a matrix, shown in the top part of Fig. 1. The parameter X_{sq} denotes the value of the qth grouping criterion of the sth learner, and it is normalized by (1). The parameter X'_{sq} denotes the normalized value of X_{sq}. In this example, C_1 is the total score of completed exercises, C_2 is the total score of tests, and C_3 is the class rank,

$$X'_{sq} = (X_{sq} - \min_{1\le s\le S} X_{sq})/(\max_{1\le s\le S} X_{sq} - \min_{1\le s\le S} X_{sq}),$$
$$\text{e.g. } X'_{11} = (70-30)/(90-30) = 0.67. \tag{1}$$

Using the TOPSIS enables obtaining the overall learning status of the sth learner (denoted as Z_s) by considering the Q grouping criteria. The process comprises the following four steps:

Step 1. Constructing a matrix regarding S learners with Q grouping criteria

The matrix facilitates obtaining the overall learning status based on multiple grouping criteria for the learners; it is constructed by allocating the learners to the top of a matrix, allocating the grouping criteria to the left of a matrix, and filling the cells <grouping criteria, learners> of the matrix with the values. The example is shown in the top part of Fig. 1.

Step 2. Determining the positive-ideal solution and negative-ideal solution for Q grouping criteria

For the qth grouping criterion, the positive-ideal solution is the positive-ideal value denoted as V_q^+, and the negative-ideal solution is the negative-ideal value denoted as V_q^-. Each grouping criterion has both the positive-ideal value and negative-ideal value. The values depend on whether the grouping criteria are benefit or cost objectives, as shown in (2) and (3). For example, the total score of completed exercises (C_1) and the total score of tests (C_2) are benefit objectives, whereas the class rank (C_3) is a cost objective.

$$V_q^+ = \begin{cases} 1, & C_q \in \text{Benefit} \\ 0, & C_q \in \text{Cost} \end{cases}$$
$$\text{e.g. } V_1^+ = 1, V_2^+ = 1, V_3^+ = 0 \tag{2}$$

$$V_q^- = \begin{cases} 0, & C_q \in \text{Benefit} \\ 1, & C_q \in \text{Cost} \end{cases}$$
$$\text{e.g. } V_1^- = 0, V_2^- = 0, V_3^- = 1. \tag{3}$$

Step 3. Using Euclidean distance to compute two measures for S learners

As shown in (4), the first measure denoted as D_s^+ is used to compute the distance (Euclidean) from the Q positive-ideal values for the Q grouping criteria for the sth learner. As shown in (5), the second measure denoted as D_s^- is used to compute the distance (Euclidean) from the Q negative-ideal values for the Q grouping criteria for the sth learner. The weights of the grouping criteria are considered for both measures. The example is shown in the bottom part of Fig. 1, where the weights (W_1 and W_2) are 0.3 for the total score of completed exercises (C_1) and the total score of tests (C_2), and the weight (W_3) is 0.4 for the class rank (C_3),

$$D_s^+ = \left(\sum_{q=1}^{Q}(X'_{sq} - V_q^+)^2 W_q\right)^{1/2}$$
$$\text{e.g. } D_1^+ = ((0.67-1)^2 \times 0.3 + (0.50-1)^2 \times 0.3 + (0.33-0)^2 \times 0.4)^{1/2} = 0.39, \tag{4}$$

$$D_s^- = \left(\sum_{q=1}^{Q}(X'_{sq} - V_q^-)^2 W_q\right)^{1/2}$$
$$\text{e.g. } D_1^- = ((0.67-0)^2 \times 0.3 + (0.50-0)^2 \times 0.3 + (0.33-1)^2 \times 0.4)^{1/2} = 0.62. \tag{5}$$

Step 4. Computing the relative closeness to the ideal solution for S learners

The ideal solution is the ideal value of the overall learning status, which requires considering the positive-ideal and negative-ideal values of multiple grouping criteria. The relative closeness to the ideal value is the value of the overall learning status (Z_s), which involves considering the distance from the positive-ideal values and distance from the negative-ideal values for multiple grouping criteria, as shown in (6). Values that are nearer to the positive-ideal and further from the negative-ideal indicate a higher overall learning status. The example is shown in the bottom part of Fig. 1,

$$Z_s = D_s^- / \left(D_s^+ + D_s^-\right)$$
$$\text{e.g. } Z_1 = 0.62/(0.39+0.62) = 0.61. \tag{6}$$

Based on the mean of Z_s of S learners (denoted as $\bar{Z}$) and the standard deviation of Z_s of S learners (denoted as Z^σ), all learners are arranged into three subsets by applying (7) according to their overall learning statuses (Z_s). The parameter $\boldsymbol{L}^{\mathrm{B}}$ denotes a subset of learners whose overall learning statuses are below medium (i.e., low). The parameter $\boldsymbol{L}^{\mathrm{M}}$ denotes a subset of learners whose overall learning statuses are in the middle (i.e., medium). The parameter $\boldsymbol{L}^{\mathrm{A}}$ denotes a subset of learners whose overall learning statuses are above medium (i.e., high). Given that N^{B} denotes the number of learners of the subset $\boldsymbol{L}^{\mathrm{B}}$, N^{M} denotes the number of learners of the subset $\boldsymbol{L}^{\mathrm{M}}$, and N^{A} denotes the number of learners of the subset $\boldsymbol{L}^{\mathrm{A}}$. For example, the learner L_5 belongs to the subset $\boldsymbol{L}^{\mathrm{B}}$, and N^{B} is 1; the learners L_1, L_2, L_4, and L_6 belong to the subset $\boldsymbol{L}^{\mathrm{M}}$, and N^{M} is 4; and the learners L_3 and L_7 belong to the subset $\boldsymbol{L}^{\mathrm{A}}$, and N^{A} is 2,

$$\begin{aligned}
\boldsymbol{L}^{\mathrm{B}} &= \{L_s | Z_s < \bar{Z} - Z^\sigma\} \\
\boldsymbol{L}^{\mathrm{M}} &= \{L_s | \bar{Z} - Z^\sigma \le Z_s \le \bar{Z} + Z^\sigma\} \\
\boldsymbol{L}^{\mathrm{A}} &= \{L_s | \bar{Z} + Z^\sigma < Z_s\} \\
&\text{e.g.} \\
\boldsymbol{L}^{\mathrm{B}} &= \{L_s | Z_s < 0.49 - 0.34\} = \{L_5(0.00)\} \\
\boldsymbol{L}^{\mathrm{M}} &= \{L_s | 0.49 - 0.34 \le Z_s \le 0.49 + 0.34\} \\
&= \{L_1(0.61), L_2(0.55), L_4(0.23), L_6(0.29)\} \\
\boldsymbol{L}^{\mathrm{A}} &= \{L_s | 0.49 + 0.34 < Z_s\} = \{L_3(0.91), L_7(0.86)\}.
\end{aligned} \tag{7}$$

Because S learners divided into T required groups that have a particular group size, denoted as λ, and a number of remaining learners, denoted as θ (i.e., $S \div T = \lambda \cdots \theta$), the structure of the group is obtained using (8), based on the group size (λ). The parameter R^{B} denotes the number of learners whose overall learning statuses are low in the group. The parameter R^{M} denotes the number of learners

		R^{B}	R^{M} (+1)	R^{A}		
Individual$_1$ = [	G_1 :	L_5,	L_2, L_6,	L_7	]	, $E_1 = 4$
	G_2 :	L_4,	L_1,	L_3		, $E_2 = 3$
Individual$_2$ = [	G_1 :	L_4,	L_1, L_2,	L_7	]	, $E_1 = 4$
	G_2 :	L_5,	L_6,	L_3		, $E_2 = 3$

Fig. 2. Chromosome encoding of feasible solutions.

whose overall learning statuses are medium in the group. The parameter R^{A} denotes the number of learners whose overall learning statuses are high in the group. For example, when the required groups (T) are 2, then the group size (λ) is 3 and the remaining learners (θ) are 1 (i.e., $7 \div 2 = 3 \cdots 1$),

$$\begin{aligned} & R^{\mathrm{B}} \cong N^{\mathrm{B}} / \left(N^{\mathrm{B}} + N^{\mathrm{M}} + N^{\mathrm{A}}\right) \times \lambda \\ & R^{\mathrm{M}} \cong N^{\mathrm{M}} / \left(N^{\mathrm{B}} + N^{\mathrm{M}} + N^{\mathrm{A}}\right) \times \lambda \\ & R^{\mathrm{A}} \cong N^{\mathrm{A}} / \left(N^{\mathrm{B}} + N^{\mathrm{M}} + N^{\mathrm{A}}\right) \times \lambda, \\ & \text{where } R^{\mathrm{B}} + R^{\mathrm{M}} + R^{\mathrm{A}} = \lambda \text{ and } R^{\mathrm{M}} \geq R^{\mathrm{B}}, R^{\mathrm{A}} \geq 1 \\ & \text{e.g.} \\ & R^{\mathrm{B}} \cong 1/(1+4+2) \times 3 \cong 1 \\ & R^{\mathrm{M}} \cong 4/(1+4+2) \times 3 \cong 1 \\ & R^{\mathrm{A}} \cong 2/(1+4+2) \times 3 \cong 1. \end{aligned} \tag{8}$$

Based on the determined structure of the group, the number of learners for the aforementioned three subsets is adjusted by applying (9) and considering the number of remaining learners (θ). The parameter $N^{\mathrm{B}'}$ denotes the adjusted number of learners whose overall learning statuses are low. The parameter $N^{\mathrm{M}'}$ denotes the adjusted number of learners whose overall learning statuses are medium. The parameter $N^{\mathrm{A}'}$ denotes the adjusted number of learners whose overall learning statuses are high.

Accordingly, all learners are rearranged into three subsets by applying (10), depending on the order of their overall learning statuses (Z_s) in the class. The parameter $\boldsymbol{L}^{\mathrm{B}'}$ denotes an adjusted subset of learners whose overall learning statuses are low. The parameter $\boldsymbol{L}^{\mathrm{M}'}$ denotes an adjusted subset of learners whose overall learning statuses are medium. The parameter $\boldsymbol{L}^{\mathrm{A}'}$ denotes an adjusted subset of learners whose overall learning statuses are high. The remaining learners (θ) are arranged into the subset $\boldsymbol{L}^{\mathrm{M}'}$ on the basis of following normal distribution. For example, $N^{\mathrm{B}'}$ is 2 and the learners L_4, L_5 belong to the subset $\boldsymbol{L}^{\mathrm{B}'}$; $N^{\mathrm{M}'}$ is 3 and the learners L_1, L_2, L_6 belong to the subset $\boldsymbol{L}^{\mathrm{M}'}$; and $N^{\mathrm{A}'}$ is 2 and the learners L_3, L_7 belong to the subset $\boldsymbol{L}^{\mathrm{A}'}$,

$$\begin{aligned} & N^{\mathrm{B}'} = R^{\mathrm{B}} / \left(R^{\mathrm{B}} + R^{\mathrm{M}} + R^{\mathrm{A}}\right) \times (S - \theta) \\ & N^{\mathrm{M}'} = R^{\mathrm{M}} / \left(R^{\mathrm{B}} + R^{\mathrm{M}} + R^{\mathrm{A}}\right) \times (S - \theta) + \theta \\ & N^{\mathrm{A}'} = R^{\mathrm{A}} / \left(R^{\mathrm{B}} + R^{\mathrm{M}} + R^{\mathrm{A}}\right) \times (S - \theta) \\ & \text{e.g.} \\ & N^{\mathrm{B}'} = 1/(1+1+1) \times (7-1) = 2 \\ & N^{\mathrm{M}'} = 1/(1+1+1) \times (7-1) + 1 = 3 \\ & N^{\mathrm{A}'} = 1/(1+1+1) \times (7-1) = 2 \end{aligned} \tag{9}$$

$$\begin{aligned} & \boldsymbol{L}^{\mathrm{B}'} = \{L_s | order(s) \leq N^{\mathrm{B}'}\} \\ & \boldsymbol{L}^{\mathrm{M}'} = \{L_s | N^{\mathrm{B}'} < order(s) \leq N^{\mathrm{B}'} + N^{\mathrm{M}'}\} \\ & \boldsymbol{L}^{\mathrm{A}'} = \{L_s | N^{\mathrm{B}'} + N^{\mathrm{M}'} < order(s) \leq N^{\mathrm{B}'} + N^{\mathrm{M}'} + N^{\mathrm{A}'}\}, \\ & \qquad \text{where} \underset{1 \leq s \leq S}{\text{order}} Z_s \text{ in ascent} \\ & \qquad \text{e.g.} \\ & \qquad \underset{1 \leq s \leq S}{\text{order}} Z_s = \{0.00(L_5), 0.23(L_4), 0.29(L_6), \\ & \qquad\qquad 0.55(L_2), 0.61(L_1), 0.86(L_7), 0.91(L_3)\} \\ & \boldsymbol{L}^{\mathrm{B}'} = \{L_s | order(s) \leq 2\} = \{L_5, L_4\} \\ & \boldsymbol{L}^{\mathrm{M}'} = \{L_s | 2 < order(s) \leq 2+3\} = \{L_6, L_2, L_1\} \\ & \boldsymbol{L}^{\mathrm{A}'} = \{L_s | 2+3 < order(s) \leq 2+3+2\} = \{L_7, L_3\}. \end{aligned} \tag{10}$$

Additionally, given $\boldsymbol{E} = \{E_t\}$, where $\boldsymbol{E}$ denotes a set of T group sizes, and E_t denotes the tth group size in $\boldsymbol{E}$ and is obtained by applying (11) and considering the number of remaining learners (θ). Because the remaining learners (θ) are arranged into the subset $\boldsymbol{L}^{\mathrm{M}'}$, a learner is added to R^{M} for θ groups. For example, considering one remaining learner for two required groups, the first group has 3 + 1 (E_1) members with (low: 1, medium: 1 + 1, and high: 1); and the second group has 3 (E_2) members with (low: 1, medium: 1, and high: 1).

$$\begin{aligned} & E_t = \begin{cases} \lambda + 1 \leftrightarrow (R^{\mathrm{B}}, R^{\mathrm{M}} + 1, R^{\mathrm{A}}), & \theta \neq 0 \text{ and } t \leq \theta \\ \lambda \quad \leftrightarrow \quad (R^{\mathrm{B}}, R^{\mathrm{M}}, R^{\mathrm{A}}), & \text{otherwise} \end{cases} \\ & \text{e.g. } E_1 = 3 + 1 \leftrightarrow (1, 1+1, 1); E_2 = 3 \leftrightarrow (1, 1, 1). \end{aligned} \tag{11}$$

5.2 Chromosome Encoding and Initialization

The chromosome (individual) represents a feasible solution for grouping and is encoded as a two-dimensional matrix. Each gene represents a learner (L_s), and each row represents a group (G_t) with E_t members. Each group is formatted based on the determined structure of the group. For initialization, each gene is randomly assigned a learner from the subsets $\boldsymbol{L}^{\mathrm{B}'}$, $\boldsymbol{L}^{\mathrm{M}'}$, or $\boldsymbol{L}^{\mathrm{A}'}$ according to what part of R^{B}, R^{M}, or R^{A} this gene belongs to. The example is shown in Fig. 2.

5.3 Fitness Evaluation

The fitness evaluation facilitates evaluating individual fitness to determine the quality of grouping solutions. An enhanced TOPSIS is used to compute the quality of grouping solutions, as shown in the following steps 1-5.

Step 1. Constructing a matrix regarding I individuals with Q grouping criteria

The population size, denoted as I, represents the number of individuals (grouping solutions), $1 \leq i \leq I$, where i denotes the iteration of I. Based on multiple grouping criteria, the matrix is constructed and is used to determine the quality of grouping solutions. Fig. 3 shows an example, in which C_1 is the total score of completed exercises, C_2 is the total score of tests, and C_3 is the class rank.

Step 2. Determining the positive-ideal solution and negative-ideal solution for Q grouping criteria

As aforementioned, the positive-ideal solution is the positive-ideal value (V_q^{+}), and the negative-ideal solution is the

		C_1	C_2	C_3	D_t^+	D_t^-	RC_t	F_i
Individual$_1$	G_1	0.42	0.46	0.58	0.57	0.43	0.43	0.698
	G_2	0.61	0.56	0.39	0.41	0.59	0.59	
Individual$_2$	G_1	0.63	0.54	0.46	0.44	0.57	0.57	0.690
	G_2	0.33	0.44	0.56	0.59	0.41	0.41	

Fig. 3. Matrix regarding *I* individuals with *Q* grouping criteria.

negative-ideal value (V_q^-) for the qth grouping criterion. The values depend on whether the grouping criteria are benefit or cost objectives, as shown in (2) and (3). For example, the total score of completed exercises (C_1) and the total score of tests (C_2) are benefit objectives, whereas the class rank (C_3) is a cost objective.

Step 3. Using Euclidean distance to compute two measures for T groups

For each group, its overall status of each grouping criteria is obtained by applying (12), where $\overline{G_tC_q}$ denotes the mean of the qth grouping criterion of the tth group, and X_{sq}^t denotes the value of the qth grouping criterion of the sth learner who is in the tth group. For example, the members in the first group (G_1) of the first grouping solution (individual$_1$) are the learners L_2, L_5, L_6, and L_7, and their total scores of completed exercises (C_1) are 0.50, 0.00, 0.17, and 1.00, respectively,

$$\overline{G_tC_q} = \left(\sum_{s=1}^{E_t} X_{sq}^t\right)/E_t$$
$$\text{e.g. } \overline{G_1C_1} = (0.50 + 0.00 + 0.17 + 1.00)/4 = 0.42. \quad (12)$$

The first measure denoted as D_t^+ is used to compute the distance (Euclidean) from the Q positive-ideal values for the Q grouping criteria for the tth group, as shown in (13). The second measure denoted as D_t^- is used to compute the distance (Euclidean) from the Q negative-ideal values for the Q grouping criteria for the tth group, as shown in (14). In addition, the weights of the grouping criteria are considered for both measures. The example is shown in Fig. 3, where the weights (W_1 and W_2) are 0.3 for the total score of completed exercises (C_1) and the total score of tests (C_2), and the weight (W_3) is 0.4 for the class rank (C_3)

$$D_t^+ = \left(\sum_{q=1}^{Q}(\overline{G_tC_q} - V_q^+)^2 W_q\right)^{1/2}$$
$$\text{e.g. } D_1^+ = ((0.42-1)^2 \times 0.3 + (0.46-1)^2 \times 0.3 + (0.58-0)^2 \times 0.4)^{1/2} = 0.57 \quad (13)$$

$$D_t^- = \left(\sum_{q=1}^{Q}(\overline{G_tC_q} - V_q^-)^2 W_q\right)^{1/2}$$
$$\text{e.g. } D_1^- = ((0.42-0)^2 \times 0.3 + (0.46-0)^2 \times 0.3 + (0.58-1)^2 \times 0.4)^{1/2} = 0.43. \quad (14)$$

Step 4. Computing the relative closeness to the ideal solution for T groups

The ideal solution is the optimal group formation. The relative closeness to the optimal group formation is the quality of the group formation, which is determined by the distance from the positive-ideal values and the distance from the negative-ideal values for multiple grouping criteria, as shown in (15). The parameter RC_t denotes the quality of group formation of the tth group. The nearer to the positive-ideal values and the further from the negative-ideal values RC_t is, the higher is the quality of group formation when multiple grouping criteria are considered. The example is shown in Fig. 3

$$RC_t = D_t^- / \left(D_t^+ + D_t^-\right)$$
$$\text{e.g. } RC_1 = 0.43/(0.57+0.43) = 0.43. \quad (15)$$

Step 5. Computing the fitness for I individuals

The individual fitness is the quality of grouping solutions. Based on the mean of RC_t of T groups (denoted as $\overline{RC}$) and the standard deviation of RC_t of T groups (denoted as RC^σ), the quality of a grouping solution is obtained by applying (16). The parameter F_i denotes the quality of a grouping solution of the ith individual, and ω denotes both weights. Based on the quality of group formations (RC_t), the formula (16) involves determining the whole quality of all groups, and entails determining the difference of quality among the groups. The higher the quality of group formation is and the smaller the quality difference of the group formation among all groups, the higher is the quality of grouping solutions employing tradeoff multi-objective grouping optimization. An example is shown in Fig. 3. Note that, the computational result obtained by the proposed fitness evaluation is between 0 and 1

$$F_i = \omega \times \overline{RC} + (1-\omega) \times (1 - RC^\sigma)$$
$$\text{e.g. } F_1 = 0.5 \times 0.51 + 0.5 \times (1 - 0.12) = 0.698. \quad (16)$$

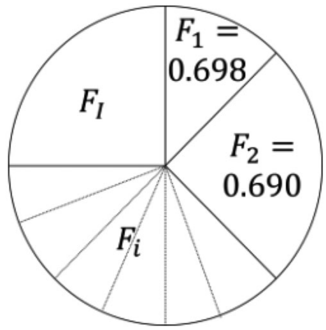

Fig. 4. Roulette wheel selection.

5.4 Selection

The selection preserves favorable grouping solutions to continue quality promotion. A roulette wheel, which is based on the principle of natural selection, is a widely used method for facilitating the survival of individuals which are more suited to propagating offspring. As shown in Fig. 4, the roulette wheel selection is composed of all individuals in the population (I) in which an individual with a higher degree of fitness (F_i) has a higher probability of survival (thereby continuing the evolution). In other words, the grouping solution with a higher quality (F_i) has a higher probability to be selected for continuing the promotion

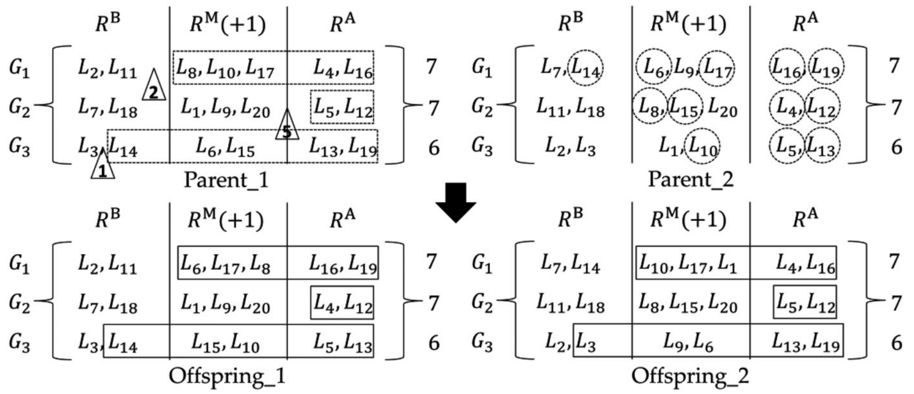

Fig. 5. Example of an enhanced C1 crossover.

when using the roulette wheel. For example, the first grouping solution (individual$_1$) has a higher probability than the second grouping solution (individual$_2$).

5.5 Crossover

The crossover facilitates interchanging the group members between two grouping solutions to alter their quality. Based on the C1 crossover modification of Moreno et al. [1], the crossover was enhanced in the current study by considering the determined structure of a group as follows. Any two individuals are selected as parents according to the crossover probability (denoted as P_c). The number of crossover points is the number of required groups (T). Each crossover point is randomly generated according to the group size (E_t). For the first offspring, the genes (L_s) at the left side of the crossover points are fixed in the same manner as the first parent, and the genes (L_s) at the right side of the crossover points are re-sorted for the respective part of R^{B}, R^{M}, and R^{A}, according to their positions in the second parent. Fig. 5 shows the example. The number of crossover points is three, and the crossover points are 2, 5, and 1.

5.6 Mutation

The mutation facilitates exchanging the group members within a grouping solution to change the group's quality. In addition, the mutation was enhanced by considering the determined structure of a group as follows. For any individual, three parts of R^{B}, R^{M}, and R^{A} are selected according to the mutation probability (denoted as P_{m}). The number of mutation points depends on the number of selected parts. Any two mutation points are randomly generated in the different rows (G_t) for each selected part. For the offspring, two genes (L_s) of two mutation points within the same part exchange their positions; Fig. 6 shows the example. The parts R^{B} and R^{M} are selected for mutation. The number of mutation points is four, where two mutation points are the learner L_7 in the group G_2 and the learner L_3 in the group G_3 for the part R^{B}, and the other two mutation points are the learner L_9 in the group G_2 and the learner L_{15} in the group G_3 for the part R^{M}.

5.7 System Implementation

To assist teachers in directly adopting the proposed approach in their teaching, a web-based group support system was implemented. As shown in Fig. 7, the teachers access the developed system through a user interface, which includes the settings for the class, grouping criteria, and parameters of the GA, as well as the grouping solution. The settings can be adjusted through the various components of the system, as shown in Fig. 8.

The teachers select the class whose students need to be allocated into groups by using the class-management module combined with a student database. When typing the number of needed groups, the size of each group is automatically determined. Subsequently, the teachers select the student characteristics by using the criterion-management module combined with a student-characteristic database; the weights of the grouping criteria are simultaneously determined. Next, the teachers determine the parameters of the GA as default values or other values to facilitate the identification of a grouping solution. Note that, the parameters of the GA might be different due to different teaching classes and learning scenarios. The default values produced by the developed system are current optimal, and they are obtained from the feedback of grouping results in past teaching classes and learning scenarios. Hence, the teachers need not to test the parameters of the GA; on the contrary, they are able to concentrate on designing learning activities. The process of this identification is based on the model of a GA with the TOPSIS. According to this model, first, the data from the learning-portfolio database (according to the

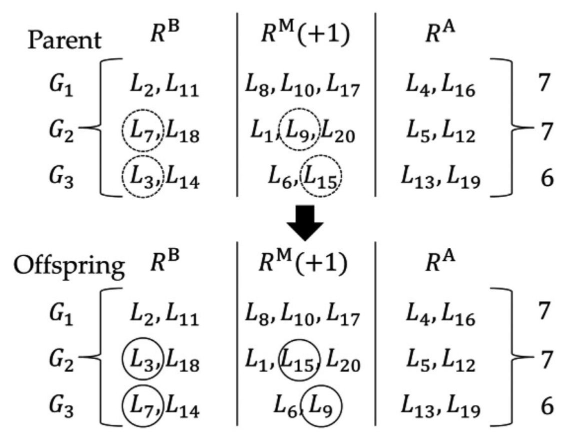

Fig. 6. Example of an enhanced mutation.

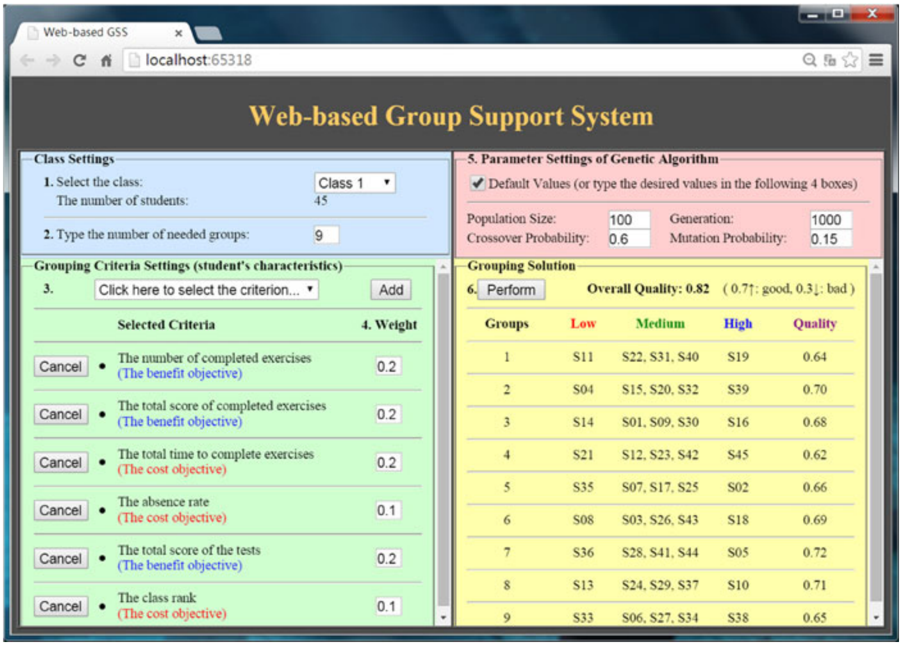

Fig. 7. System implementation based on the proposed approach.

students of the selected class and the selected student's characteristics) are loaded. Next, the search for grouping solutions commences according to the determined parameters of the GA. Finally, the search result provides the teachers with the ideal grouping solution. In addition, the quality of the grouping solution and the quality of the group formation of each group are provided as a reference.

For the students, the grouping solutions determined using the proposed approach meet the requirements of heterogeneous intra-group and homogeneous inter-group and prevent inadequate grouping. Each group contains students of distinct levels, namely low, medium, and high, which is consistent with the distribution of students in the class. Thus, within the groups, members who are more capable can help those who require support. In addition, because groups are based on multiple grouping criteria, they are balanced and contain students with a similar performance; this leads to a reduced difference among the groups. Thus, because competition is fairer among the groups, the learning motivation is higher. Teachers typically administer a high number of students and must consider multiple grouping criteria, which are related to student characteristics and can be defined as benefit and cost objectives. The developed system reduces their workload and the likelihood of mistakes, and provides them with high-quality grouping solutions. Consequently, the teachers have more time to concentrate on pedagogical theories for designing CL activities, thereby increasing the quality and efficiency of their teaching.

6 Performance Analysis

To verify the proposed approach based on an enhanced GA with the TOPSIS (EGA), performance experiments were conducted to facilitate comparison with two competing approaches, the GA-based approach of Moreno et al. [1] and the Random approach. The same fitness evaluation with the TOPSIS were employed in these two competing approaches, to obtain the individual fitness in the same scale, for a fair comparison. Two experiments involved using a simulated dataset and a real dataset, separately. The experiments were implemented using C programming language performed on a laptop equipped with a 2.10 GHz Core i7 CPU and 4.00 GB RAM.

6.1 Experimental Materials

The simulated dataset consisted of 50 learners ($S = 50$) and six grouping criteria ($Q = 6$) with three benefit and three cost objectives. The values of the six grouping criteria of the 50 learners and the weights of the six grouping criteria were randomly generated. The real dataset included online learning behavior collected from 117 learners by Chiu et al. [38]. This dataset comprised 117 learners ($S = 117$) and eight grouping criteria ($Q = 8$) with four benefit and four cost objectives; the weights of the eight grouping criteria were randomly generated.

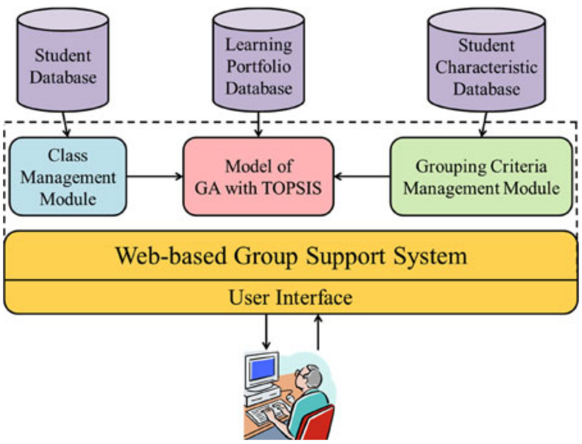

Fig. 8. Architecture of the developed system.

TABLE 1
Parameter Settings

Population size (I)	20 / 40 / 80 / 100
Generation (O)	200 / 400 / 800 / 1,000
Crossover probability (P_c)	0.6
Mutation probability (P_m)	0.15
Group size (λ)	3 / 4 / 5
Fitness weight (ω)	0.5
Number of trials	100

6.2 Parameter Settings

To ensure an unbiased performance comparison, the values of the related parameters (shown in Table 1) were identical for the EGA as well as the GA and Random approaches for each dataset. The probabilities of crossover and mutation were determined according to Moreno et al. [1]. Regarding the group size, Slavin [39] indicated that two to six members are suitable for group formation to perform the CL; therefore, the performance experiments were constructed in groups containing three to five members. The number of trials was 100 to ensure high reliability.

6.3 Comparison Results

Table 2 shows the performance comparison using the simulated dataset, and Table 3 shows the performance comparison using the real dataset. The results of the EGA were superior to those of the GA and Random approaches under conditions of different population sizes, generations, and group sizes. Concerning solution quality (SQ), the EGA yielded a higher SQ than did the GA and Random approaches, which means that the solution provided by the EGA was superior. Regarding the standard deviation of the inter-group (SDE), the SDE of the EGA was lower than that of the GA and Random approaches. Concerning the standard deviation of the intra-group (SDA), the SDA of the EGA was higher than that of the GA and Random approaches. Based on these two results, the solution identified by the EGA exhibited a lower SDE and a higher SDA, which means that the inter-group was more homogeneous and the intra-group was more heterogeneous. Regarding executing time (ET; measured in seconds), the EGA required a shorter ET than did the GA. Each experimental result represented an average of 100 trials.

Figs. 9, 10, and 11 show the search process using the simulated dataset with group sizes of 3, 4, and 5 members,

TABLE 2
Performance Comparison Using the Simulated Dataset

Parameters			EGA				GA				Random			
λ	I	O	SQ	SDE	SDA	ET	SQ	SDE	SDA	ET	SQ	SDE	SDA	ET
3	20	200	0.7876	0.0017	0.3923	0.0562	0.7858	0.0053	0.3806	0.0601	0.7742	0.0274	0.2961	0.0002
	40	400	0.7879	0.0012	0.3925	0.2193	0.7866	0.0038	0.3821	0.2413				
	80	800	0.7880	0.0008	0.3926	0.8750	0.7873	0.0024	0.3831	0.9586				
	100	1,000	0.7881	0.0006	0.3927	1.3486	0.7876	0.0017	0.3836	1.4803				
4	20	200	0.7879	0.0010	0.3707	0.0501	0.7870	0.0030	0.3631	0.0554	0.7765	0.0231	0.3138	0.0006
	40	400	0.7881	0.0006	0.3707	0.1984	0.7876	0.0017	0.3635	0.2174				
	80	800	0.7883	0.0004	0.3707	0.7822	0.7879	0.0011	0.3640	0.8589				
	100	1,000	0.7883	0.0003	0.3707	1.2198	0.7881	0.0007	0.3633	1.3268				
5	20	200	0.7880	0.0009	0.3601	0.0501	0.7873	0.0023	0.3561	0.0558	0.7781	0.0202	0.3212	0.0006
	40	400	0.7882	0.0005	0.3602	0.1927	0.7878	0.0014	0.3568	0.2189				
	80	800	0.7883	0.0003	0.3602	0.7675	0.7880	0.0008	0.3566	0.8507				
	100	1,000	0.7883	0.0002	0.3603	1.1920	0.7882	0.0006	0.3570	1.3468				

TABLE 3
Performance Comparison Using the Real Dataset

Parameters			EGA				GA				Random			
λ	I	O	SQ	SDE	SDA	ET	SQ	SDE	SDA	ET	SQ	SDE	SDA	ET
3	20	200	0.7674	0.0054	0.0701	0.2665	0.7587	0.0225	0.0650	0.2814	0.7498	0.0399	0.0557	0.0009
	40	400	0.7683	0.0037	0.0701	1.0559	0.7601	0.0198	0.0658	1.0978				
	80	800	0.7691	0.0023	0.0700	4.1532	0.7611	0.0179	0.0662	4.2802				
	100	1,000	0.7694	0.0016	0.0700	6.4023	0.7622	0.0159	0.0667	6.6779				
4	20	200	0.7685	0.0036	0.0684	0.2496	0.7618	0.0168	0.0649	0.2681	0.7526	0.0347	0.0580	0.0011
	40	400	0.7692	0.0022	0.0684	0.9917	0.7626	0.0152	0.0652	1.0611				
	80	800	0.7697	0.0012	0.0685	3.9418	0.7639	0.0127	0.0656	4.2405				
	100	1,000	0.7700	0.0008	0.0685	6.0892	0.7647	0.0112	0.0659	6.5368				
5	20	200	0.7690	0.0027	0.0673	0.2454	0.7632	0.0142	0.0643	0.2499	0.7544	0.0314	0.0589	0.0007
	40	400	0.7695	0.0016	0.0673	0.9642	0.7644	0.0120	0.0646	0.9655				
	80	800	0.7699	0.0009	0.0673	3.6773	0.7651	0.0105	0.0650	3.8105				
	100	1,000	0.7701	0.0006	0.0672	5.9099	0.7663	0.0081	0.0651	5.9167				

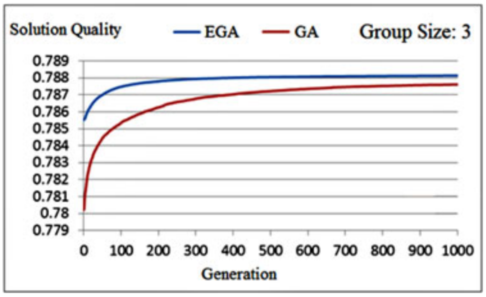

Fig. 9. Search process using the simulated dataset with a group size of three members.

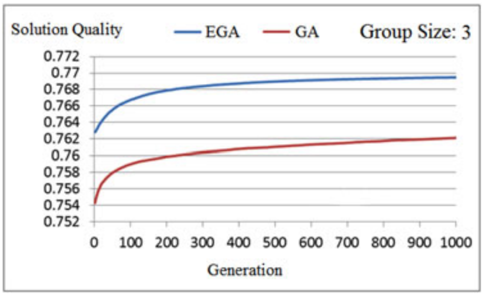

Fig. 12. Search process using the real dataset with a group size of three members.

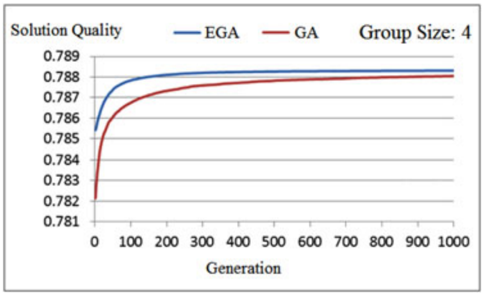

Fig. 10. Search process using the simulated dataset with a group size of four members.

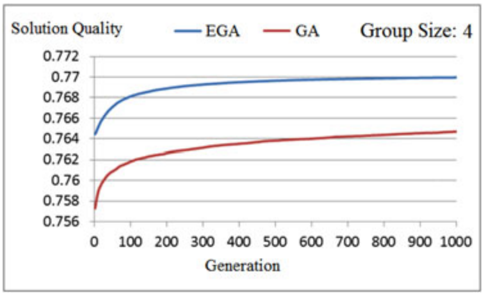

Fig. 13. Search process using the real dataset with a group size of four members.

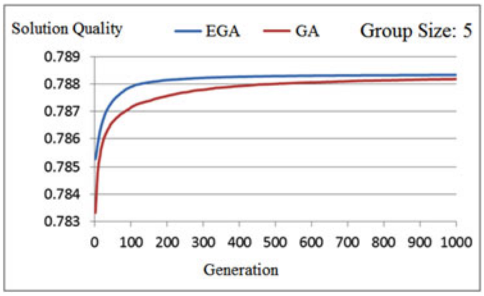

Fig. 11. Search process using the simulated dataset with a group size of five members.

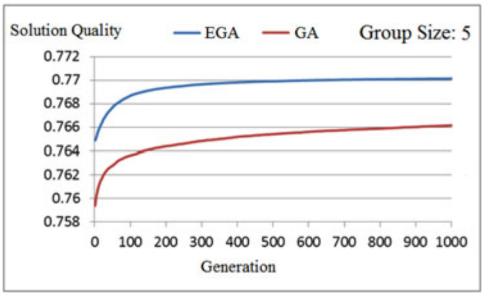

Fig. 14. Search process using the real dataset with a group size of five members.

respectively; Figs. 12, , 13, and 14 show the search process using the real dataset with group sizes of 3, 4, and 5 members, respectively; in Figs. 9, 10, 11, 12, 13, and 14, the population size is 100 and the generation is the 1,000th. Based on the search curve depicting the SQ, the EGA exhibited a search efficiency that was superior to that of the GA algorithm and a convergence that was quicker. Therefore, the EGA achieved the enhancement proposed in this study. Concerning initialization, the EGA exhibited a higher SQ than did the GA algorithm, which means that the EGA had superior search ability for the problem at the beginning of the search process. This result demonstrates that the EGA exhibited a unique initialization behavior, different to that of the simple random initialization.

7 Study on Collaborative Learning Activities

To validate the grouping strategy based on the proposed approach for CL, an experimental study was conducted with 90 freshmen of two classes (taught by the same teacher), enrolled in a C-programming course in the Department of Computer Science and Information Engineering at a Taiwanese university.

7.1 Competing Grouping Strategy and Considered Grouping Criteria

In the selected course, the teacher has typically used a self-organized grouping strategy for CL. However, based on a self-organized grouping strategy certain teams tend to be composed of students with a close friendship, and the remaining teams tend to be composed of the remaining students without much motivation. In other words, such grouping results do not satisfy all students. Hence, the proposed grouping strategy was compared with the strategy of self-organized grouping.

Forty-five participants in one class were assigned to the experimental group and employed the proposed grouping strategy; the remaining 45 participants in the other class were the control group and employed the self-organized grouping strategy. According to the results of previous performance experiments, the SQ is most favorable with a group size of five members; therefore, the number of

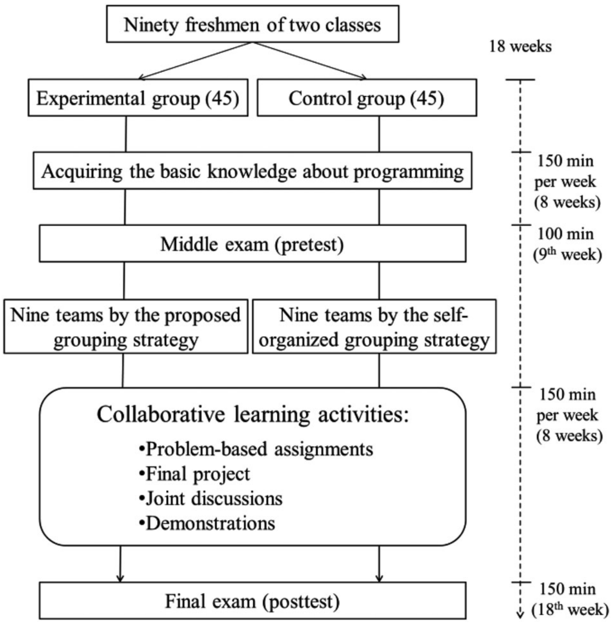

Fig. 15. Procedure of the overall learning activity.

members in a team was five for both groups, consistent with Moreno et al. [1]. Both the experimental and control groups comprised nine teams.

For the experimental group, the grouping criteria and related parameter settings were considered. Regarding the grouping criteria, six student characteristics collected during acquiring the required basic knowledge about programming were employed. These comprised three benefit and three cost objectives:

1. Number of completed exercises (benefit).
2. Total score of completed exercises (benefit).
3. Total time to complete exercises (cost).
4. Absence rate (cost).
5. Pretest score (benefit).
6. Class rank (cost).

The weight of each grouping criteria was identical. Regarding the parameter settings, the crossover probability was 0.6, the mutation probability was 0.15, and ω was 0.5; the values were the same as in the performance experiments; the population size was 100 and the generation was the 1,000th because such a SQ was superior in the performance experiments.

7.2 Procedure Design and Measuring Tools

Fig. 15 shows the procedure of the overall learning activity, which lasted for 18 weeks. First, two classes were assigned to be the experimental group and the control group. In the first eight weeks (Weeks 1-8, 150 min per week), all students were engaged in acquiring the required basic knowledge about programming through individual learning. During these eight weeks, their learning statuses were recorded by system to be subsequently employed as grouping criteria. In the ninth week, all students took a middle exam (the pretest) of 100 min, and the results were used to assess their basic knowledge about programming.

Subsequently, two groups were allocated into multiple teams in preparation for the CL activities, in which the experimental group employed the proposed grouping strategy and the control group employed the self-organized grouping strategy. In the following eight weeks (Weeks 10-17, 150 min per week), the CL activities were conducted to give the teams one problem-based assignment per week and a final project. For the CL activities, each member had to join discussions and interact with their teammates to complete the task. All teams were asked to demonstrate their results and report the contribution of each member to validate the member's participation. In the 18th week, all students were asked to take a final exam (the posttest) of 150 min to assess their knowledge level and proficiency in coding.

Regarding the measuring tools, both the middle and final exam represented learning achievement with a perfect score of 100. The middle exam consisted of 60 percent written test and 40 percent coding test, and the final exam consisted of 40 percent written test and 60 percent coding test.

TABLE 4
t-Test Results for Two Groups on the Pretest

	Number of students	Mean	Standard deviation	t
Experimental group	45	69.40	13.66	0.062
Control group	45	69.22	13.64	

7.3 Statistical Results

To test whether there was a statistically significant difference between the experimental and the control groups regarding the pre- and posttest, the independent-sample t-test was performed for both groups by using SPSS (ver. 17) software.

Table 4 shows the t-test results of the pretest for both groups. For the experimental group the mean was 69.40 and the standard deviation was 13.66; for the control group the mean was 69.22 and the standard deviation was 13.64. According to $t = 0.062$ ($p > .05$), it was determined that there was no statistical evidence to determine a significant difference between the means of both groups regarding the pretest. In other words, students in both the experimental and control groups had a statistically equivalent basic knowledge of programming.

Table 5 shows the t-test results of the posttest for both groups. For the experimental group the mean was 81.38 and the standard deviation was 17.53; for the control group the mean was 58.36 and the standard deviation was 26.65. According to $t = 4.841$ ($^{***}p < .001$), it was determined that there was statistical evidence of a significant difference between the means of both groups regarding the posttest. In other words, the students in both the experimental and

TABLE 5
t-Test Results for Two Groups on the Posttest

	Number of students	Mean	Standard deviation	t
Experimental group	45	81.38	17.53	4.841^{***}
Control group	45	58.36	26.65	

$^{***}p < 0.001$

control groups had statistically different knowledge levels and proficiency in coding.

As shown in Table 5, the experimental group exhibited a higher mean and a lower standard deviation than the control group regarding the posttest. In other words, all students in the experimental group exhibited a learning achievement that was superior to that of the students in the control group. Furthermore, the control group exhibited a higher standard deviation, which is consistent with the unbalanced phenomenon observed in self-organized grouping strategies.

8 Discussion and Conclusion

CL has been studied and its effect on learning performance has been investigated. The grouping problem has become crucial in a CL environment. The grouping problem is complex, and forming adequate groups is difficult because various grouping criteria related to learner statuses must be satisfied, often with a high numbers of learners. Several studies have addressed the certain research questions of grouping problem, and the consideration for a number of learner characteristics has been arisen. Such multi-objective grouping problem is with conflicting grouping objectives, involving the benefit objective (e.g. learning achievement) and cost objective (e.g. class rank) which are conflicting in different directions.

Such group problem was defined as a tradeoff multi-objective grouping optimization in this study, and a novel approach based on the enhancement of a GA with the TOPSIS was proposed to facilitate it. Moreover, a web-based group support system based on the proposed approach was developed to assist instructors in effectively and efficiently allocating learners to groups, regarding homogeneous inter-group and heterogeneous intra-group, while achieving tradeoff multiple grouping objectives related to learner characteristics, and considering the distribution of learners in the class.

To verify the proposed approach, a performance analysis was conducted by comparing the proposed approach with two competing approaches (i.e., the GA [1] and Random approaches). The results of the comparison are as follows. In contrast to GA approach, the proposed approach leads to not only a superior SQ but also shorter ET for grouping, while ensuring inter-group that are more homogeneous and intra-group that are more heterogeneous. Although the Random approach requires the least ET, it yields the least favorable SQ. Moreover, regarding the insight into the search process, the proposed approach is superior to GA approach in search efficiency and convergence. Hence, the proposed approach is not only more effective than the GA and Random approach but also more efficient than a GA.

To validate the grouping strategy based on the proposed approach, a study on CL was conducted with 90 participants, who were allocated to experimental and control groups. The statistical results are as follows. The students in both groups exhibited no statically significant difference regarding their basic knowledge before participating in the CL activity; however, after having participated in CL activities in designated teams, they exhibited statically significant differences regarding their knowledge level and proficiency in coding. In contrast to the students of the control group, all students in the experimental group exhibited superior learning achievement during the overall CL activity. Hence, as a grouping strategy, the proposed approach with developed system enabled the students to achieve higher learning performance with a statistical significance, by facilitating team formations that were more appropriate.

Furthermore, the conducted study also collected the feedback through a simple interview for students in both the experimental group and the control group, as follows. In terms of self-evaluation, in the experimental group, no students (0 percent) had negative experiences in working with their teammates, and all students were motivated to work in their teams; but in the control group, some students (33 percent) had negative experiences in working with their teammates, and they were not motivated to work in their teams. In terms of peer-evaluation, most students (89 percent) of the experimental group thought teammates had a positive attitude toward their teams, but only some students (53 percent) of the control group thought teammates had a positive attitude toward their teams. In terms of team-evaluation, in the experimental group, most students (89 percent) satisfied the grouping results by the developed system with proposed grouping strategy, and they felt comfortable to the teamwork during CL activities; but in the control group, only some students (53 percent) satisfied the grouping results by the self-organized grouping strategy, and the others (47 percent) felt uncomfortable to the teamwork during CL activities. To sum up, most students of the experimental group gave the positive feedback, describing the developed system with proposed grouping strategy as a valuable and fair tool to group them.

However, this study has several limitations. The experimental results were obtained only from the selected course and selected classes. In other words, the effectiveness of the developed system with the proposed approach was validated only through the conducted experimental study. Consequently, additional experimental studies are required to prove the effectiveness of the proposed approach. For example, the developed system could be applied to various types of course and on a large scale.

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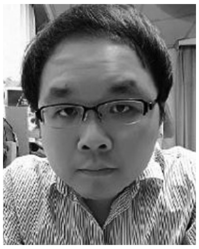

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