Using a genetic algorithm to determine optimal complementary learning clusters for ESL in Taiwan

Ya-huei Wang, Yi-Chang Li, Hung-Chang Liao

Department of Applied Foreign Languages, Chung-Shan Medical University, Department of Medical Education, Chung-Shan Medical University Hospital, No. 110, Sec. 1, Jian-Koa N. Road, Taichung 402, Taiwan

Department of Health Services Administration, Chung-Shan Medical University, Department of Medical Management, Chung-Shan Medical University Hospital, No. 110, Sec. 1, Jian-Koa N. Road, Taichung 402, Taiwan

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ABSTRACT

This paper proposes a strategy for using students' complementary competencies in cooperative learning to increase their English learning performance. The concept of complementary learning is based on the idea that teaching is learning. The foundation of the complementary learning concept is composed of three stages proposed to derive the optimal learning clusters—input stage, genetic algorithm (GA) stage, and output stage. In tests and verification of the feasibility of using optimal complementary learning clusters in increasing students' English learning outcome, comparisons between the experimental group (the optimal complementary learning clusters) and the control group showed that students in the experimental group had higher performances in listening, speaking, and reading competencies than those in the control group. Finally, according to the respective importance weights of different English competencies in different learning objectives, the fuzzy linguistic terms were applied to derive optimal complementary learning clusters to maximize students' learning outcome.

1. Introduction

Cluster learning is a form of cooperative learning. The benefit of cluster learning is that students can acquire, share, and coordinate knowledge through a cooperative process. McConnell's research (1996) demonstrates that active and cluster learning methods increase students' knowledge and learning outcomes in the classroom. Besides, cluster learning brings the additional benefit of preparing students to be accustomed to future professional environments. Nichols and Miller's research (1994) reveals that students in a cooperative classroom exhibit significantly greater gains in achievement, efficacy, intrinsic values, and learning goal orientation than those in traditional lecture clusters. Kirschner, Beers, Boshuizen, and Gijseelaers (2008) conducted a series of experiments on cluster learning, showing that a tool capable of facilitating negotiation between individual standpoints can bring positive effects by achieving common ground. However, according to Wong (2004), tension and disadvantage may arise when managing two types of cluster learning simultaneously, because a higher level of group cohesion may increase distal learning but in some ways decrease local learning. In other words, when students engage in both local learning and distal learning, distal learning may inhibit local learning from accomplishing a higher level of group efficiency.

Language-learning activities incorporate cluster learning primarily in conversation exercises. Oxford and Ehrman (1995) explored adult language learning strategies in intensive foreign language programs. They examined how an individual's language learning strategies correlate with their language competency and with diverse cognitive, affective, and social factors. Optimal learning groups are created taking into consideration the students' language competency and individual characteristics. Ghaith and Yaghi (1998) compared the effect of cooperative learning on English language acquisition with the individualistic instructional approach mainly based on textbook exercises. The research results show that low achievers in the experimental groups make more gains than their high-achieving counterparts in the same groups, without inhibiting their high-achieving group mates. Wood and Head (2004) applied a problem-based leaning to biomedical English instruction, which is a problem-oriented, cluster-based, and student-centered approach.

Hinger (2006) revealed that group cohesion is a powerful indicator of group motivation, and an intensive course can create a supportive classroom environment that enhances group cohesion. An appropriate distribution of instructional time may also enhance group cohesion and group learning. Yang and Chen (2007) investigated the effect of the integration of multimedia technology in English teaching activities—cluster e-mailing, a Web-based course,
an e-mail writing program, English homepage design, video-conferencing, and chat room discussion. Their study shows that students with different learning backgrounds can enhance each other’s educational experiences by bringing different perspectives to English language learning. Krecic and Grmek (2008) explored grammar and elementary school teachers’ perceptions of cooperative learning to assess the value of cluster learning in comparison to individual learning. Their results show that cluster learning enables participants to compare their opinions with those of others, yielding deeper insight.

In summary, the above literature review indicates that cluster learning can enhance participants’ learning outcome and communication. However, participants in the above-mentioned groups are clustered mainly based on their similar characteristics, rather than their complementary characteristics. This paper takes students’ complementary competencies into consideration while clustering students for a course of English as a Second Language (ESL). For example, the student who has better English-speaking competency is clustered with the student who has better English writing competency but worse speaking competence and the student who has better reading competence but worse speaking competence. Hence, these students with distinct English competencies and skills are clustered into the same group to teach and learn from each other, exchanging their learning methods and experiences in English speaking, reading, and writing. The concept of complementary learning is based on the idea that teaching is learning. When someone else is teaching, students are taught what they do not know; by teaching, they become aware of the shortcomings in their own knowledge. Based on the concept of complementary learning, this paper proposes three stages to derive the optimal cluster for complementary learning: input stage, genetic algorithm (GA) stage, and output stage. The input stage served to collect students’ initial English scores and normalize the data of their scores. The GA stage used a genetic algorithm to derive the result for the output stage. The output stage focused on finding the optimal clusters for implementing complementary learning. Section 2 contains a detailed description of the three stages for obtaining the optimal complementary learning clusters. Section 3 presents the empirical experiment for verifying the performance of complementary learning clusters. Section 4 uses fuzzy linguistic rules to derive complementary learning cluster to maximize students’ learning outcome according to the respective importance weights of different English competencies in different learning objectives. Section 5 gives the conclusion of this paper.

2. Three stages to obtain the optimal clusters for complementary learning

In this research, three stages—input stage, GA procedure, and output stage—were developed to obtain the optimal clusters for complementary learning. The following Fig. 1 is a detailed description of the three stages.

2.1. Stage I. Input

The input stage included the following two steps. Step 1 was to collect the students’ initial English scores and Step 2 was to normalize the data of the students’ initial English scores.

2.1.1. Step 1. Collecting students’ initial English scores

Forty-five students at a university in central Taiwan were selected as the experimental sample. To assess the students’ initial English levels, it was necessary to collect their initial English scores. The students’ English scores of the previous semester—in listening, speaking, and reading—served as their initial English scores, and distinguished the English proficiencies between students in these three competencies to further derive optimal clusters for implementing complementary learning.

2.1.2. Step 2. Normalizing the data of students’ initial English scores

This step normalizes students’ initial English scores to avoid the various effects of adopting different standards for measuring students’ distinctive and distinguished English proficiencies. The following Eq. (1), \( Z_i (0 \leq Z_i \leq 1) \), was the method of normalization.

\[
Z_i = \frac{X_i - \text{min}}{\text{max} - \text{min}},
\]

where

\[
X_{ij}^{\text{max}} = \max(X_{ij}, \ i = 1, 2, \ldots, 45), \ j = 1 \text{ for listening, 2 for speaking, 3 for reading}
\]

and

\[
X_{ij}^{\text{min}} = \min(X_{ij}, \ i = 1, 2, \ldots, 45).
\]

The notation is described as follows:

- \( Z_i \) is the \( i \)th student in the \( j \)th normalization score in English proficiency.
- \( X_{ij} \) is the \( i \)th student in the \( j \)th initial score in English proficiency.
- \( X_{ij}^{\text{max}} \) represents the maximal scores in the \( j \)th initial score in English proficiency.
- \( X_{ij}^{\text{min}} \) represents the minimal scores in the \( j \)th initial score in English proficiency.

Table 1 shows the normalization scores for 45 students in different English proficiency sections.

2.2. Stage II. GA procedure

2.2.1. GA procedure

GA is a search technique used to find optimal solutions to problems, based on the Darwinian principle of “survival of the fittest” and genetics in biological systems (Goldberg, 1989). The optimal solution is derived after going through a series of iterative computations to deal with large search spaces randomly and efficiently to obtain near optimal solutions to complex problems (Fogel, 1994). The GA generates a series of alternate solutions, which are represented by a chromosome. The series of alternate solutions serve as solution options to the problem until acceptable results are obtained. A GA can quickly derive an optimal solution without examining all possible solutions to the problem. To obtain an optimal solution, a typical GA uses three main operators—selection, crossover, and mutation—to improve the fitness of a population of guesses toward convergence (Goldberg, 1989).

Based on the above GA methodology, in this paper, the GA was performed to obtain the optimal clusters for complementary learning. The tests utilized the Evolver 4.0 software for Excel as the solving tool. Order-based GA was adopted as the solving method to determine the optimal complementary learning clusters. The solving method of order-based GAs provides a permutation of a list of items, deriving the optimal order from a list of items, which is called order crossover (Davis, 1985, 1991). Order crossover is regarded as one of the best solving methods in terms of quality and speed (Larranaga, Kuijpers, Murga, Inza, & Dizdarevic, 1999).

According to Davies (1991), order crossover creates an offspring by the following procedure.

Input: two parents.
Output: a child.

Step 1: Select a substring from parent 1.
Step 2: Produce a child by copying the substring into its corresponding positions.

Step 3: Delete the nodes already in the substring from parent 2. The resulting sequence of nodes includes the nodes that the child needs.

Step 4: To produce an offspring, place the nodes into the child’s unfixed positions from left to right according to the order of the sequence.

Crossover rate can be varied from 0 to 1. Fig. 2 shows an example of an order crossover operator.

The three Steps for setting an order-based GA are as follows.
2.2.2. Step 1. Setting the initial population size, mutation rate, and crossover operator

Hundred strings were randomly generated to establish an initial population. When the GA is applied to optimize complementary learning clusters, the essential operators—including reproduction, crossover, and mutation—should be determined in advance. This study adopted a roulette wheel approach as the selection procedure. The mutation rate was determined automatically. The crossover rate was set as 0.5.

2.2.3. Step 2. Determining the fitness function

The fitness function was constructed to obtain optimal complementary learning clusters. In grouping clusters, there should be a maximum complementarity within each cluster and a minimum total variance among clusters.

Eq. (4) shows the formulation for the fitness function.

\[
\text{Max} \left( \frac{1}{\sum_{j=1}^{9} \sum_{c=1}^{5} (Z_{cj}^k - \overline{Z}_j)^2} \right) / \sum_{j=1}^{9} \left( \frac{1}{\sum_{c=1}^{5} (Z_{cj} - \overline{Z}_j)^2} \right)
\]

where

- \( c \) = cluster number (\( c = 1, 2, \ldots, 9 \)), and
- \( l \) = student number within a cluster (\( l = 1, 2, 3, 4, 5 \)).

The notation is described as following:

- \( Z_{cj}^k \) is the \( l \)th student in the \( j \)th normalization score in English proficiency when he/she is assigned to \( c \)th cluster with the \( l \)th number.
- \( \overline{Z}_j \) is the \( j \)th average normalization score in English proficiency in \( c \)th cluster.

2.2.4. Step 3. Setting the terminal condition

The stopping condition of the GA procedure was set at 1000 iterations, or when the change in the previous 100 iterations was less than 1%.

2.3. Stage III. Output

In this stage, the optimal clusters for complementary learning in ESL were determined. The final fitness value was 265.004 when the order-based GA was in terminal condition. Table 2 shows the result of the optimal clusters.

3. Empirical experiment

To evaluate the performance of the optimal complementary learning clusters, two homogenous and normally distributed classes were chosen as the experimental group (45 students) and the control group (42 students). The subjects were college students in central Taiwan who had studied English for at least 6 years since junior high school. Prior to the evaluation of the learning clusters, the students took an English pretest, based on the database of the General English Proficiency Test (GEPT), to assess their initial English proficiencies in listening, speaking, and reading.

Both the control group and the experimental group took an English pretest covering listening, speaking, and reading. The test contained 50 multiple-choice questions in the listening and reading sections. Every question was worth two points, totaling 100 points for each the listening and reading sections. There were 10 questions in the speaking section, with each question worth 10 points, making 100 points total. For the experimental group, the listening pre-test results showed that the mean and standard deviation were 39.63 and 3.00. For the control group, the mean was 40.36 and the standard deviation was 4.21. The independent sample t-test showed that there were no significant differences between these two groups in the listening section. In the speaking section, the mean of the experimental group was 43.14 and standard deviation was 3.22. The mean of the control group was 42.46 and standard deviation was 4.04. The t-test result (\( t = 0.87 \) and \( p \)-value = 0.39) showed that there was no significant difference between these two groups in the speaking section. In the reading section, the mean of the experimental group was 64.05 and standard deviation was 4.42. The mean of the control group was 62.37 and standard deviation was 4.49. The t-test result (\( t = 1.75 \) and \( p \)-value = 0.08) showed there was no significant difference between the two groups in the reading section. Hence, The English proficiency pretest results show that both groups were homogeneous in the listening, speaking, and reading sections.

Nine clusters were determined to determine the effect of optimal complementary learning clusters, setting the experimental group students’ English scores of the last semester as their initial English proficiencies. Table 2 illustrates the nine optimal clusters for complementary learning in ESL for the experimental group. In contrast, students in the control group were allowed to form their own learning clusters. They formed eight clusters, in which there were five students in six of the learning clusters and six students in two of the learning clusters.

The teaching material used in the study was from an intermediate level teaching reference—World Link: Developing English Fluency, published by Thomson ELT (Stempleski, Curtis, Douglas, & Morgan, 2005), a leading provider of materials for English language teaching and learning throughout the world. World Link is a core series of textbooks intended to develop students’ listening, speaking, and reading competencies.

The experiment took place during the 2009 fall semester. It was implemented in two class periods per week for 12 weeks. Students had to spend half of every period participating in cluster discussion. Both groups received the same teaching materials, homework, and evaluation procedure, but were situated in different cluster arrangements.

The two student groups were compared in the post-test to evaluate their learning achievements after 12 weeks of instruction. The post-test also covered listening, speaking, and reading sections, using the same test style as the pre-test. The post-test results show that in the listening section, the mean of the experimental group was 58.64 and the standard deviation was 4.68. The mean of the control group was 56.21 and the standard deviation was 4.33. The t-test showed that there was a significant difference (\( t = 2.51, p \)-value = 0.01 < 0.05) between the two groups in the listening section. In the speaking section, the mean of the experimental group was 72.01 and the standard deviation was 4.19. The mean of the control group was 68.54 and the standard deviation was 3.88. The t-test showed that there was a significant difference (\( t = 3.99, p \)-value = 0.00 < 0.01) between the two groups in the speaking section. In the reading section, the mean of the experimental group was 81.80 and the standard deviation was 4.47. The mean of the control group was 78.17 and the standard deviation was 4.23.

Table 2

<table>
<thead>
<tr>
<th>Cluster number</th>
<th>Student number</th>
<th>Cluster number</th>
<th>Student number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{1, 9, 16, 20, 45}</td>
<td>6</td>
<td>{10, 13, 26, 30, 34}</td>
</tr>
<tr>
<td>2</td>
<td>{2, 8, 22, 29, 35}</td>
<td>7</td>
<td>{11, 15, 23, 25, 43}</td>
</tr>
<tr>
<td>3</td>
<td>{3, 18, 29, 40, 41}</td>
<td>8</td>
<td>{14, 27, 31, 42, 44}</td>
</tr>
<tr>
<td>4</td>
<td>{4, 7, 17, 21, 25}</td>
<td>9</td>
<td>{19, 24, 32, 36, 37}</td>
</tr>
<tr>
<td>5</td>
<td>{6, 12, 28, 33, 38}</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fitness value: 265.004.
The t-test showed that there was a significant difference ($t = 3.89$, $p = 0.00 < 0.01$) between the two groups in the reading section. Table 3 shows the pre- and post-test results.

The above data shows that all the post-test mean scores of the experimental group were significantly higher than those of the control group in the listening, speaking, and reading sections. Hence, it can be concluded that the students arranged in optimal complementary learning clusters outperform those clusters formed by the students.

### 4. Fuzzy linguistic terms used in consideration of different weights in different competencies

In real class instruction, teachers may prioritize certain English skills over others. For instance, in an English reading comprehension class, the teacher would probably place more weight on reading competence than other competencies. Hence, in order meet the course objective, distinct competence/skill areas (e.g. listening, speaking, or reading) should be assigned different weights in different courses to prioritize certain skills and goals. That is, the weight of each competence should vary in different courses. Therefore, when forming optimal complementary learning clusters, the teachers should give specific weight to each competence in different courses to meet learning objectives. Furthermore, this study used the fuzzy linguistic terms coined by Chen and Hwang (1992) to solve the problems of assigning different weights to different competencies in different courses. The development of a scale system of linguistic terms resulted in the proposal of a comprehensible and feasible system for practical application. The formal scale system enables the conversion of linguistic terms into their corresponding fuzzy numbers (Tong & Su, 1997).

This study further used the fuzzy ranking method to transform linguistic terms to fuzzy numbers. According to the fuzzy numbers, the relative high, medium, and low importance fell on a simple scale of three values. The high fuzzy number was 0.833, the medium was 0.500, and the low was 0.166. Using a simple calculation, this paper normalized these three fuzzy numbers as the fuzzy weights. The normalized fuzzy weight was $0.556 \times (w_1, w_2, w_3)$, and the other two fuzzy weights were 0.333 and 0.111. After obtaining three fuzzy weights, we assigned the three weights to listening, speaking, and reading competencies to derive nine clusters. Each cluster was composed of five members with different competencies. There was a maximum complementarity within each cluster. However, there was a minimum total variance among clusters. Based on the assignments of the three weights to the three competencies, six (3!) combinations were derived and are shown in Table 4.

### 5. Conclusion

This research studies how to form optimal learning clusters using students’ complementary competencies to increase their English learning performance. Based on the concept of complementary learning, three stages—input stage, GA stage, and output stage—were proposed to derive the optimal learning clusters. In the input stage, students’ initial English scores on listening, speaking, and reading competencies were collected and normalized. Later, a GA based on experimental group students’ initial English proficiencies was used to obtain the nine optimal complementary learning clusters. The posttest results show that students in the experimental group have higher performances in the listening, speaking, and reading sections than those in the control group. Furthermore, this study used the fuzzy ranking method to transform linguistic terms into three fuzzy numbers, and to normalize these three fuzzy numbers as the fuzzy weights. While teaching, the tea-
cher took the respective importance weights of different English competencies into consideration. To derive the complimentary clusters, three different weights were assigned to listening, speaking, and reading competencies. These weights may aid future cluster grouping, when different English competencies are weighed in different learning contents to meet different learning objectives.

This study outlines an alternative solving method using an order-based GA to derive the optimal complementary learning clusters, in which students can both teach and learn from each other, having equal contributions to the clusters according to their complementary competencies. We hope that this paper may serve as a solid base for future research for using order-based GA techniques to derive optimal learning groups to maximize students’ learning outcomes. Future studies may apply order-based GA techniques to derive the optimal complementary clusters for ESL classes, factoring in students’ complementary characteristics, such as gender, personality, learning styles, cognitive styles, etc.

References


