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A Cyclic-genetic-algorithm Approach to Composing Heterogeneous Groups of Students

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***Abstract* – In this paper, the proposed model is described to demonstrate how to mix students in a heterogonous way and equally balance groups in terms of the educational background and assessment of students. A cyclic genetic algorithm (CGA) is employed in the model to mimic the natural process of evolution to achieve the optimized solution. In order to keep population diversity in the CGA, a particular cycle shift operator and self-crossover operator are presented. The model can be used as a starting point for considering both educational background and peer assessments in the formation of heterogeneous groups of students.**

Keywords* – *Cooperative learning, Cyclic genetic algorithm, Group formation, Heterogeneous groups, Peer assessment.

1. Introduction

e-Learning has revolutionized the educational sector and become the most popular online tool for educators. Pappas [1] claims that approximately 46% of college students are taking at least one course online. Moreover, the e-Learning industry has a promising future. Pappas also suggested that by 2019, e-Learning will be used by roughly half of all college classes. Current e-Learning techniques do not adequately support groups formed in cooperative learning (CL), resulting in decreased student development and inspiration [2]. Nevertheless, traditional online courses are constructed in a way that does not motivate student interaction. Hence, e-Learning often encourages students to study alone. However, cooperative learning is a flourishing teaching strategy and is an important part of many courses. It also helps students solve exercises faster and more easily. This is why several educators are now interested in fostering student interaction in online courses. Some researchers have documented the benefits and effectiveness of cooperative learning in higher education [3], [4]. Johnson et al. [5] argued that cooperative learning allows students to achieve better levels of thought and that they are more able to maintain information longer compared to when studying alone.

In order to develop effective teams of students, peers must understand their own personal attributes as well as appreciate the contributions of others. This is one of the most challenging topics for educators. Bradley and Hebert [6] suggested that personality types are also an important factor in successful teams and performances. Supported by Johnson and colleagues [7], they described a process to select group members. The main objective of the process is to clarify a team's competence and enhance group outcomes. The process determines those member actions that were useful and those that were not. Moreover, educational factors, such as grades and knowledge background, have been used in group formation methods. Johnson et al. indicated that there are many ways of constructing group, such as monitoring the quality of the interaction among members related to the tasks they are responsible for and observing the feedback among peers as they work. The work of Kuh et al. [8] has focused on improving cooperative learning for students by peer assessment. They mention that teachers need to comprehend the value on assessment as it helps to improve teaching, learning, and institutional effectiveness. Furthermore, as noted by Spiller [9], peer assessment is widely used across higher education. Miller et al. demonstrated the use of peer assessment in their survey questions for forming groups of students [10]. Gatfield illustrated the efficiency and effectiveness of learning outcomes in

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group work and peer assessment [11]. He confirmed that peer assessment within a group can satisfy most students in class. Moreover, he suggested that tension can arise due to concerns about the assessment of group tasks. Additionally, Burdett conducted a case study to gain information about the attitude of peers to group work [12]. The survey revealed that most students feel positive about group work. Moreover, Oakley et al. stated that peer assessment is often used for enhancing team performance and adjusting team grades for individual performances [13].

There is a list of tools in an e-Learning environment for cooperative group composition. Most of them involve the level of knowledge, grades, and educational attributes of individual students. In the computer-supported DIANA system [15], Wang et al. proposed a method for the heterogeneous grouping of students (students of different levels) into small groups by choosing multiple criteria to avoid the construction of exceptionally weak groups. The DIANA system uses genetic algorithms to generate student groups with fairness, equity, and flexibility. Christodoulopoulos and Kyparisia [14] demonstrated a web-based group formation tool in e-Learning environments; however, their system is not based on peer attitudes. Moreover, Hwang et al. in [16] presented a web-based application (ITED III) that uses multiple criteria for group composition. Subsequently, Moreno et al. [17] proposed the group formation of dissimilar students using a genetic algorithm by translating three student characteristics, namely knowledge levels, communicative skills, and student leadership skills. Jozan et al. [18] presented a method for finding optimal groups using genetic algorithms. Various features governing the quality of group formation were used as the decision criterion. Gogoulou et al. proposed a tool for forming homogeneous, heterogeneous and mixed groups of learners using genetic algorithms and the learners' personality and performance attributes [19]. Finally, Lin et al. used algorithms employing Particle Swarm Optimization (PSO) for composing well-structured collaborative learning groups [20].

The studies discussed above show that there are several group formation techniques for cooperative learning. However, few works construct optimized groups by a heuristic search based on educational background data and peer assessments. More importantly, the ability to balance various variables among heterogeneous groups is vital. As a result, the search for an optimized group composition of all students is a time-consuming process, especially for a large group of students. It is therefore necessary to use an appropriate heuristic search in the model. In order to overcome the difficulties underlined here, we present a model of group formation considering 1) educational background and 2) peer assessments employing a cyclic genetic algorithm. The proposed model is designed for teachers in e-Learning environments to construct heterogeneous groups of students with fairness in terms of educational background and assessment of student.

There are five parts in this paper, including this section. In section 2, the concept of assessment in cooperative learning is detailed. Section 3 illustrates the proposed model of student formation in detail. Section 4 demonstrates how a cyclic genetic algorithm of the proposed model can be used to optimally allocate dissimilar students, low-ability students, and high-ability students, into appropriate groups. Finally, section 5 presents conclusions and further research.

2. Peer Assessment in Cooperative Learning

Cooperative learning has been found to be a successful teaching strategy at all levels. Several studies, including the work by Burdett [12] and Hanrahan and Isaacs [21], have shown that most students who have participated in group work feel positive about cooperative learning. Accordingly, cooperative learning has become an essential teaching arrangement for heterogeneous groups of students [22-23]. Dotson [24] has argued that in cooperative learning the most widely used method for group formation is heterogeneous grouping. The groups generated by heterogeneous grouping may contain a mixture of students at different levels of knowledge and ethnic diversity. Therefore, there are many more tasks involved in cooperative learning than just grouping students. In the class, dissimilar students must work in a group to complete assigned tasks to achieve an objective by means of discussion. They need to share their experiences and knowledge while they are working together. Furthermore, all members are responsible for the learning of their teammates as well as their own.

As documented by Spiller [9], peer feedback is very useful in schools as it involves students offering feedback to one another in order to improve the quality of their work. In this way, student knowledge and performances will be improved as well.

Hanrahan and Isaacs [21] have also stated that peer-assessment helps students to contribute constructively in collaborative learning. It is also a way of assessing the work of students for feedback while minimizing the cost in staff time. Additionally, the benefit of peer assessment in cooperative learning has clear implications for both theory and practice. However, peer and self-assessment still need to be implemented on a case-by-case basis in different subjects and contexts.

3. Forming Heterogeneous Groups

Suppose a class comprises n students. This class must become heterogeneous regarding the prior knowledge, educational background, personal experiences, and pretest scores of the students. We define the mathematical term as follows.

3.1 Definition

A set of students is denoted $S = \{s_1, s_2, \dots, s_n\}$ Each student s_i , $1 \leq i \leq n$, has its own attributes, which are represented in the form of $(a_1, a_2, \dots, a_p)$ where p is the number of attributes. In addition, we attempt to divide n students into m groups with the same size. We call the group size q. Then, a set of generated groups is denoted $G = \{G_1, G_2, \dots G_m\}$, where m is the number of groups. These definitions are represented in Table 1. All groups contain all the students such that $G_i \cap G_j = \emptyset$, for all $i \neq j$.

Table 1. Definitions

S	A set of all students.
n	The number of students.
s_i	The student i-th, where $1 \leq i \leq n$.
G	The set of generated groups.
m	The number of groups.
p	The number of attributes.
G_k	The group k-th, where $1 \leq k \leq m$.
q_j	The group size of the group j-th, where $1 \leq j \leq m$.

Then, we can investigate the size of the search space in forming student groups. We start with the following formula:

$$\binom{n!}{q_1, q_2, \dots, q_m} = \frac{n!}{q_1!\, q_2! \dots q_m!}.$$

if $q = q_1 = q_2 = \dots = q_m$, then

$$\binom{n!}{q_1, q_2, \dots, q_m} = \frac{n!}{(q!)^m}.$$

And, $q = \frac{n}{m}$, we get:

$$\binom{n!}{q_1, q_2, \dots, q_m} = \frac{n!}{\left(\left(\frac{n}{m}\right)!\right)^m}.$$

Also, let L be all of the different ways of forming student groups. Given the above, we divide the above formula by $m!$. That is

$$L = \frac{n!}{\left(\left(\frac{n}{m}\right)!\right)^m \cdot m!}.$$

For example, let a class of nine students be denoted as $S = \{s_1, s_2, \dots, s_9\}$. They are divided equally into 3 smaller groups. This is $m = 3$. And, the group size becomes $q = \frac{9}{3} = 3$. Then, the different way of generating student groups is $L = \frac{9!}{\left(\left(\frac{9}{3}\right)!\right)^3 \cdot 3!} = 280$.

Moreover, student i-th has its own attributes represented in a vector field $(v_1^i, v_2^i, \dots, v_k^i)$, where k is the number of attributes. Thus, searching for the optimal solution, where the attributes among divided groups are fairly balanced, becomes more complex.

3.2 A Model for Forming Heterogeneous Groups of Students

The proposed model for forming heterogeneous groups is shown in figure 1. This figure presents the ideal flow to assist teachers to generate heterogeneous groups of students regarding educational background and peer assessments. It comprises four distinct steps; 1) setting group criteria, 2) pre-group activities, 3) peer assessments, 4) and generating heterogeneous groups.

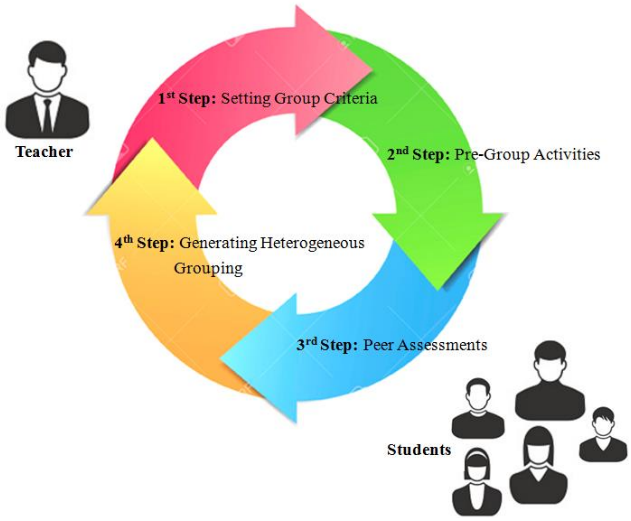

Figure 1. Model for forming heterogeneous groups.

1st Step: Setting group criteria

The criteria for forming groups are specified by a teacher considering student attributes and peer assessments. There are a variety of criteria that can be selected such as group size, type of educational backgrounds, and assessments. For our model, educational background data indicates grades received from compulsory courses based on the curriculum and the syllabus.

2nd Step: Pre-group activities

Once a set of criteria has been decided on, a sequence of pre-group activities or mini-tasks should be assigned to students. We can also call this step "pre-formed groups". Activities in this step are important since they help students to have more opportunities to get accustomed to one another. Teachers should motivate students to cooperate within the pre-groups and tell them what they need to learn. If this step is ignored, then students will not know about the working styles of their friends. Therefore, it is recommended to have at least one activity for students in this step. However, if there is only limited time available, teachers should provide at least one mini-activity for students. If this step is omitted, students in the class will have few chances to get to know each other.

3rd Step: Peer Assessments

Suppose there are p questions in an assessment questionnaire provided by a teacher. The average value of the first assessment for i-th student, denoted Ass_1^i, will be calculated after the peer assessment is done. In order to satisfy the teacher's requirements, a weighted score ($1xp$ matrix) is set, $w_i \in [0,1]$ and $\sum_{i=1}^{p} w_i = 1$. Therefore, the attribute of s_i can be represented as below.

$$s_i = (a_1^i, a_2^i, \dots, a_j^i, Ass_1^i * w_{1,}, \dots, Ass_p^{*i} * w_p)$$
$$= (a_1^i, a_2^i, \dots, a_j^i, b_1^i, b_2^i, \dots, b_p^i), \;\; for\; 1 \le i \le n$$

4th Step: Generating Heterogeneous Groups.

In the final step, a cyclic genetic algorithm is employed. As mentioned earlier for the model to establish heterogeneous groups of students, two important attributes are educational background and peer assessment. Consequently, each student is represented in a multidimensional space by a vector, in the form of a vector field $(v_1, v_2, \dots, v_k)$, where k is the number of attributes. Student i-th in a k-dimensional space is represented as a vector field $(v_1^i, v_2^i, \dots, v_k^i)$. Let a class contain n students, denoted by $S = \{s_1, s_2, \dots, s_n\}$. The students can be assigned in only one group, but each student belongs to one group. Let G denote the set of student groups, where $G = \{G_1, G_2, \dots G_m\}$ and m is the number of groups. Since m must be an interger, we define its value as follows:

$$m = \begin{cases} \lfloor n/q \rfloor & if \left(\left(\frac{n}{q} \right) - \left\lfloor \frac{n}{q} \right\rfloor \right) < 0.5, \\ \lceil n/q \rceil & otherwise \end{cases}$$

, where q is the group size.

4. A Cyclic Genetic Algorithm for Heterogeneous Groups

A cyclic genetic algorithm (CGA) is a kind of genetic algorithm (GA) that has been designed to search for solutions in a circular pattern [25]. Therefore, the main difference between a CGA and the standard GA is the structure of chromosomes. Hence, the cyclic chromosome representing the problem is encoded into an n fixed-length character string, as presented in figure 2. Each student can be assigned into any position of the string. For instance, a class of 9 students is divided into 3 groups. That is $n = 9$, $m = 3$, and $q = \lfloor 9/3 \rfloor = 3$. Let the three groups be G_1, G_2,and G_3, where $G_1 = \{s_1, s_3, s_5\}$, $G_2 = \{s_2, s_7, s_9\}$, and $G_3 = \{s_4, s_6, s_8\}$. The corresponding chromosome is illustrated in figure 3.

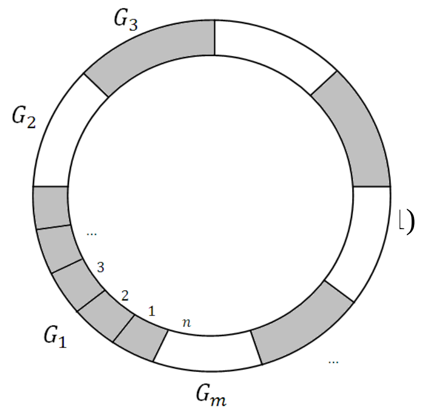

Figure 2. A cyclic chromosome, where n is the number of students.

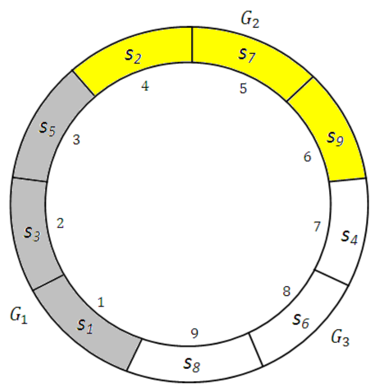

Figure 3. An example of a chromosome for 9 students, where $G_1 = \{s_1, s_3, s_5\}$, $G_2 = \{s_2, s_7, s_9\}$, and $G_3 = \{s_4, s_6, s_8\}$.

4.1 Quality of Group Formation

The formation of student groups takes into account more than one attribute; therefore, evaluating the quality of group formation is a complex task. In addition, it must be designed in the proper way corresponding to the chromosome structure. Therefore, each chromosome encoding the group formation as designed above needs to be evaluated by a fitness function in order to represent the quality of the formation. The example chromosome and its fitness evaluation is presented in figure 4., where n is the number of students and m is the number of formed groups. Based on the model in this paper, the two main objectives are:

a) creating heterogeneous groups of students
b) balancing attributes among generated groups.

4.1.1 Creating Heterogeneous Groups of Students

In order to construct student groups in a heterogeneous way, students of different levels must be mixed in the same group. This can be measured by the Euclidean distance (ED) between all of the combinations of group members. For group Gq, where $1 \le q \le m$, if there are r students, the Euclidean distance of students in Gq can be calculated as below.

$$ED\_G1(q) = \sum_{i=1}^{r-1} \sum_{k=i+1}^{r} \sqrt{(s_i - s_k)^2},$$

Suppose 'a' and 'b' are particular attributes for the formation. Then, the above equation for calculating $ED\_G1(q)$ becomes (5).

$$ED\_G1(q) = \sum_{i=1}^{r-1} \sum_{k=i+1}^{r} \sqrt{(\sum_{t=1}^{j}(a_{it} - a_{kt})^2 + \sum_{t=1}^{p}(b_{it} - b_{kt})^2} \quad (5)$$

, where a_{it} represents an attribute t of student i.

When we have computed the $ED\_G1()$ for all of the divided groups, the average value of $ED\_G1()$ for all groups encoded in chromosome$_x$ becomes

$$\frac{\sum_{i=1}^{m} ED\_G1(i)}{m} \quad (6)$$

, where m represents the number of generated groups.

4.1.2 Balancing Attributes among Generated Groups

Considering group building as a whole, it is important to balance attributes among established groups equally. Therefore, we have another aim regarding the building of heterogeneous groups of students. All heterogeneous groups of students must be reasonably at the same level. If students are divided into d groups, the vector space of group G_i where $0 < i \le d$ can be presented in (7).

$$G_i = \left(Avg(a_1^i), Avg(a_2^i), \dots, Avg(a_j^i), Avg(Ass_1^i), Avg(Ass_2^i), \dots, Avg(Ass_p^i)\right)$$
$$= (Avg(a_1^i), Avg(a_2^i), \dots, Avg(a_j^i), Avg(a_{j+1}^i), Avg(a_{j+2}^i), \dots, Avg(a_s^i)) \quad (7)$$

, where $a_{j+1}^i \leftarrow Ass_1^i,\ a_{j+2}^i \leftarrow Ass_2^i, \dots, a_s^i \leftarrow Ass_p^i$,

Consequently, the Euclidean distance (ED_G2) among vectors representing generated groups can be computed as below.

$$ED\_G2 = \sqrt{\sum_{i=1}^{m-1} \sum_{k=i+1}^{m} (Avg(a_i) - (Avg(a_k))^2} \quad (8)$$

, where *m* is the number of groups.

Let $chromosome_x$ be defined as a chromosome of a heterogeneous group of students. To make the final fitness function for the group formation, (6) and (8) presented above need to be combined. Then, the fitness value of $\mathrm{chromosome}_x$ can be formulated as follows:

$$fitness(chromosome_x) = \frac{\sum_{i=1}^{m} ED\_G(i)}{m} * Factor1 + \sqrt{\sum_{i=1}^{m-1} \sum_{k=i+1}^{m} (Avg(a_i) - (Avg(a_k))^2} * Factor2 \quad (9)$$

, where *m* is the number of groups.

$Factor1$ and $Factor2$ are arbitrary values, where $Factor1 + Factor2 = 1$. If the value of $Factor1$ is higher than that of $Factor2$, teachers aim on mixing students in the divided groups more than the balance of attributes among the groups. However, if the teacher's objective is to balance heterogeneous groups equally, the value of $Factor2$ must be higher than that of $Factor1$.

Since our model is composed of two objectives, the quality of the chromosome varies depending on the size of these values. If $Factor1 \ge Factor2$, the model based on a cyclic genetic algorithm requires chromosomes that yield the lowest fitness value. On the other hand, if $\mathrm{Factor1} < Factor2$, the model needs to generate choromosomes with the high fitness value.

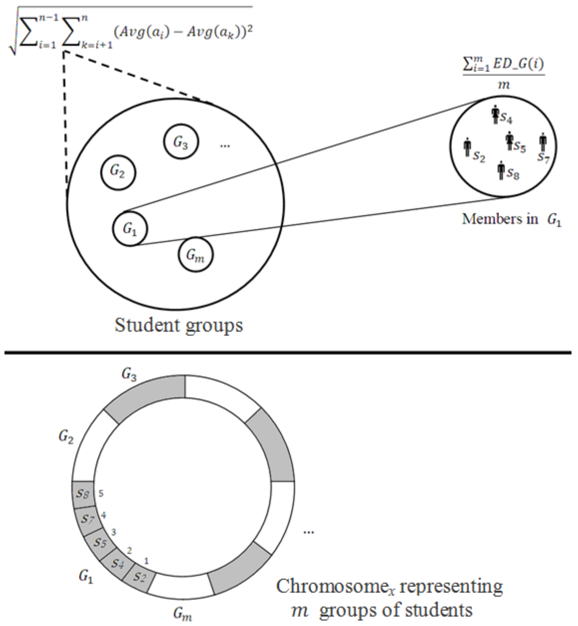

Figure 4. Chromosome and its fitness evaluation, where n is the number of students and m is the number of groups formed.

4.2 Self-Crossover Operator

In order to maintain population diversity in the model, a process called a self-crossover operation is employed. An example of a self-crossover in a cyclic chromosome is demonstrated in figure 5. The operator is mainly responsible for searching for generated offspring. The fundamental content of the operator includes two steps. Firstly, a parent chromosome is randomly chosen. Secondly, unlike the conventional crossover operator, the self-crossover operator randomly selects two portions of the parent and entirely swaps them to create an offspring. Then, a newborn offspring will be evaluated by the fitness function in (7). If the offspring yields a better fitness value than its parent, it can be selected in the next generation. This is why the crossover operation is likely to create a superior generation. Therefore, the surviving offspring of the new generation are more fit. By doing this, the most promising solution based on the fitness value will be found if it has reached the final generation. The result of the GAs may represent a fairly accurate solution to our problem.

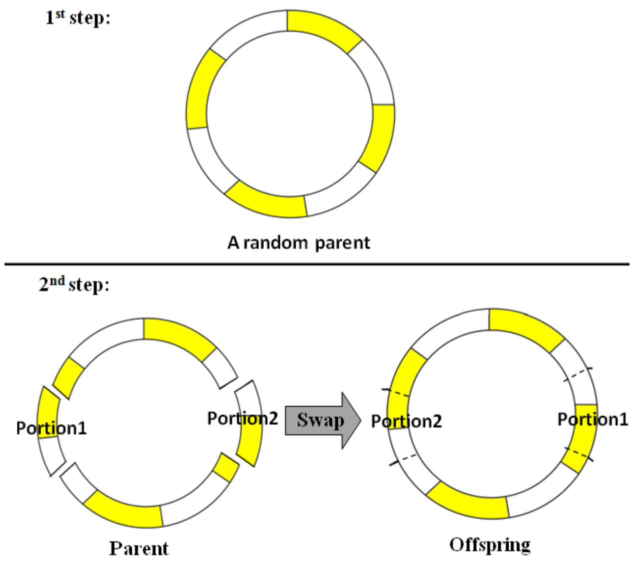

Figure 5. Example of a self-crossover operator.

4.3 Cycle Shift Operator

The aim of this operator is not to cause a mutation, but to maintain diversity in the population. Basically, it includes three steps. Firstly, one chromosome is randomly selected from the population to be a parent. Secondly, a number d is randomly chosen. Thirdly, the bit string is circularly shifted to the left to form a new offspring. However, if $d = group\ size$, then the offspring will be similar to its parent. In order to avoid this problem, $0 < d < group\ size$. For instance, lets assume that a random chromosome for nine students is the same as in figure 3., where the group size equals 3. Suppose also that we have a random number d = 2. Then, an example of a cyclic shift operator in a cyclic chromosome is illustrated in figure 6. As we can see here, the offspring generated by the cycle shift operator represents the group formation where $G_1 = \{s_6, s_8, s_1\}$, $G_2 = \{s_3, s_5, s_2\}$, and $G_3 = \{s_7, s_9, s_4\}$.

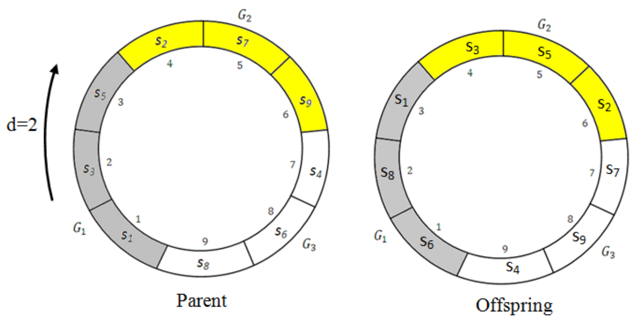

Figure 6. Example of a cyclic shift operator.

5. Conclusion and Further Work

This paper presents a model for forming mixed-ability student learning groups by using a cyclic genetic algorithm. The model takes into account more than one attribute for heterogeneous grouping. The two types of attributes employed in the model are educational background and peer assessment. Currently, we are working on the questions in order to receive peer assessments. After that, the post-study questionnaire needs to be analyzed to gather information in the established groups as well.

We hope that the model will provide an idea of how to improve the quality of heterogeneous grouping leading to better outcomes. For further research, we will apply the model to create mixed-ability groups in e-Learning environments to measure the quality and efficiency of our model to satisfy both students and teachers. Additionally, a particular case study will be investigated. We expect that heterogeneous students in the groups constructed by the model will cooperatively work and be more successful.

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