# ANOVA as Fitness Function for Genetic Algorithm in Group Composition

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***Abstract* – Establishing suitable groups of students is one of the factors considered as a key to success in group collaboration. In addition, searching for the optimal solution of the problem can be more complicated and becomes an exhaustive search, while taking into consideration the equality of the group homogeneity. However, a few approaches focus on forming groups of students based on the analysis of variance (ANOVA) to ensure that all generated groups have been drawn from a similar population. Hence, the main purpose of this research is to propose a heuristic search algorithm based on genetic algorithm (GA) referred as to 'Genetic Algorithm with ANOVA' (GANOVA) to search for best possible groupings of students in terms of educational learning styles. Furthermore, the empirical case studies demonstrate that the proposed algorithm successfully searches for forming the optimal groups of students, where the F-test value of equality of variances is near zero.**

***Keywords* –ANOVA, genetic algorithm, group composition, homogeneous grouping, optimization, Student learning styles.**

## 1. Introduction

Currently, collaborative learning is globally recognized as a successful educational approach involving a joint intellectual effort by students to improve learning quality.

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Hence, it is a daily activity and gradually becomes more important in universities. Additionally, many companies worldwide are looking for work-ready graduates. They are consequently expected to fulfill the need of graduates to be work-ready when they are about to enter the job market. That is why several universities employ collaborative learning in classes in order to develop soft skills for graduates, such as communication, interpersonal skill, technological literacy and problem-solving [1].

Cooperative learning is defined in a variety of studies. By common definition, collaborative and cooperative learning are commonly used as an effective active learning tool for group work, where students work collaboratively on assigned tasks. Ellis et al. [2] addressed that teachers tend to use collaborative learning as a tool to design teaching activities to allow students to work together. In addition, Ellis et al. have confirmed that employers in most companies wanted graduate students to be ready to work as a group of companies. De Vreede and Briggs [3] asserted that collaborative learning is an instruction method in which students work together in groups in order to achieve a common academic goal. Similarly, van der Laan Smith and Spindle [4] defined collaborative learning as a process that brings together efforts to complete desired goals. In a common definition, cooperative learning is defined as a set of processes, helping students interact to achieve learning goals. Many educational institutions worldwide have successfully applied cooperative learning to various educational environments to improve the quality of student interaction [5],[6],[7]. There are several techniques for group creation to improve knowledge-building in educational environments since researchers have investigated the impact of computer-supported collaborative learning [8],[9],[10],[11],[12],[13]. Accordingly, research efforts are dedicated to identifying the type of group-building that is more beneficial to students. Teachers may use a random method for grouping to avoid bias on forming groups of students. Some researchers presented the advantages of noticeably outperformed student-selected groups in terms of educational outcomes [14].

However, group work can frustrate students if teachers manage without careful planning and facilitation. Assigning students randomly can lead to create inequitable groups in various factors such as student personalities, abilities, or the educational backgrounds. Additionally, grouping students with diverse learning styles is an attractive topic since it has the potential to improve group performance. Using mixed learning styles to group students is more effective than using non-mixed learning style groups, according to Kayes [12].

There are tremendous reports of solving the group formation for students in various aspects. Acharya and Sinha [15] argued that an important aspect of collaborative work is its group formation. Forming an optimized group is somewhat time-consuming, if various factors, such as characteristics and educational backgrounds of students, are mainly considered in forming optimized learning groups. It is even more difficult to create optimized groups manually based on criteria to increase the potential learning of group members. There are a variety of techniques to finding an optimal solution of this type. Hwang et al. [16] successfully achieved to generate equal groups in terms of students' characteristics. In balanced groups, to ensure that all groups have been derived from similar populations, the diversity between created groups should be kept to a minimum. In order to form groups equally, it is necessary to use variance to test for a difference in means. Therefore, the value of ANOVA needs to be calculated in order to assure that all established groups have a similar composition.

To cope with the problem addressed above, therefore, the main contribution of this paper is to propose a new GA approach for composing optimal collaborative groups regarding students' characteristics. The paper is divided into five sections including this introductory section. The remaining sections of the work are structured as follows. Brief evaluations of existing literatures on group formation techniques are provided in Section 2. The relevant papers related to the optimization of methods for group formation are demonstrated in this section as well. In section 3, our mathematical model for the group formulation problem is presented. The detail of the GANOVA algorithm is demonstrated in this section. Moreover, of most importance in this section is the definition of an ANOVA-fitness function, which is used to guide the algorithm towards the optimal solution. Then, empirical studies and obtained results are discussed in Section 4 to validate the efficacy of the proposed approach. Finally, the conclusions of this work and suggestions for further works are presented in section 5.

## 2. Literature Review

Over the past several years, cooperative learning has become one of the major educational teaching strategies used in most schools and universities, as it is able to enhance student academic performance and engagement. In a cooperative learning environment, students have to work together in a group within the framework provided by teachers. The group's composition affects many aspects of group work, such as how effectively group members work together and the relevant knowledge that they can share. According to Mitchell et al. [17], group formation in classes can be done in many ways such as self selection, random selection, and selection of topic choices. One of the most common techniques to form groups is the self-selected group. The advantage of this method is that students are able to choose with whom to work. Alternatively, the group formation can be done by a random selection in which students have opportunities to learn from peers and to enhance communication skills and social soft skills. Some teachers prefer to let students self-select into groups and allow students interested in the same topic to work together. By doing this, it is feasible to mix all students together with the objective of achieving heterogeneity within groups with the goal of achieving heterogeneous grouping. However, this method does not work well for every situation. The weakness of self-selected groups is that most students are unconcerned about their classmates' background knowledge and skills. There is likely to be a degree of self-selection bias, which is a situation in which the characteristics of students cause them to choose themselves, creating unusual or unwanted conditions in the group. Moreover, students in self-selected groups tend to spend more time in socializing than working on group projects [18]. Another one, in which teachers are more in control of, is teacher selection. Teachers can manually choose which students to be added to the group.

The formation of learning groups based on characteristics relevant to the students' learning state, such as knowledge level of a related subject, has been the focus of several previous research [19]. Learning objectives, learning activities, and teaching methods are a few of the variables that Caetano et al. [20] claim have an impact on the makeup of effective groups.

In addition, Khushboo [21] argued that the performance of the group is definitely influenced by each individual of a group. Therefore, researchers have been dedicated to focusing on how computer-based methods help in the process of creating groups for students and identifying which characteristics are developed by different forms of group composition.

Furthermore, a number of conditions such as group size, group composition, and students' knowledge influence the achievement of the group as well. Regarding these factors, it is difficult to determine how to build such an optimal group that allows students to work efficiently to achieve the goals of the team. The most popular evolutionary method is genetic algorithms (GAs), which are used to implement the optimization strategies by simulating the evolution of chromosomes towards better solutions through natural selection. In GAs, a fitness function is mainly used to quantify the optimality of a solution; its value is assigned to each chromosome depending on how close it is actually to the optimal solution of the problem. In 2008, Hwang [16] presented an enhanced genetic algorithm-based approach for multi-criteria group composition (MCGC) problems. The optimization objective is calculated by the difference of the average pre-testing score between any two groups.

## 3. Research Method

First of all, we would like to address that by doing the group formation it is requested to obtain student's knowledge skills or other relevant. Teachers will be asked to collect information about their students' learning styles. As a result, if the student number in the considered classes becomes big, it takes longer to gather and justify the information about the students.

The description of GANOVA algorithm based on a GA for forming heterogeneous groups regarding specific students' characteristics is presented. Moreover, criteria for forming student groups, which are group size and students' attributes, are specified by teachers. This paper will not go into detail about the process of collecting student information. Since there are many students in a class, each student $i$ may be represented by using a vector, where $M$ is the maximum number of student's attributes,

$$s_i = (a_1, a_2, a_3 \dots, a_m) \quad (1),$$

where $a_m$ $(1 \leq m \leq M$ is a numerical value in a pre-defined range.

First, we illustrate how we encapsulate the group formation problem into a chromosome used in GA. Let $S = \{s_1, s_2, s_3 \dots, s_n\}$ be a set of students, which are required to form the groups, where $n$ is the number of students. In addition, each student $i$ is presented in the vector $s_i = (a_1, a_2, a_3 \dots, a_m)$, where $a_m$ $(1 \leq m \leq M$ is a numerical value in a pre-defined range. Suppose $G = \{Gr_1, Gr_2, Gr_3 \dots, Gr_k\}$ is the set of $k$ groups of students which are required to be formed, where the group size of $q_1 = |Gr_1|$, $q_2 = |Gr_2|$, …., $q_{k-1} = |Gr_{k-1}|$, $q_k = |Gr_k|$. And, $Gr_i \cap Gr_j = \emptyset$ for $i = 1,2, \dots, k$ and $j = 1,2, \dots k$, $i \neq j$.

### 3.1. Chromosome Representation

For this work, in the most common grouping rules, students cannot be assigned to more than one group. In other words, each student can only belong to one group. Suppose a group of $n$ students are split into $k$ different groups. Each gene of a chromosome stores only one student named $s_i$, where $s_i \subset S$ and $1 \leq i \leq n$. If a student $s_i$ is assigned to a group $k$, namely $Gr_k$, this student will appear only in the specific part of the chromosome, which are designated to $Gr_k$. As $n$ students are required to be grouped, the chromosome must be composed of $n$ sequences of different genes, which cannot be duplicated. Consequently, a chromosome structure encapsulating the group formation of $n$ students can be presented as in Figure 1.

The set of all possible solutions to our group formation problem is known as the search space. Hence, the search space is completely dependent on the problem. For this problem, the search space is $\frac{n!}{(\frac{n}{k}!)^k \cdot k!}$, where $n$ is a number of students and $k$ is the number of groups. If a number of students is big, the search space will be big. For solving such a problem like this, we need to set a bigger size for the initial population for GAs. This is because the greater the initial population size, the greater the chance that GAs will contain a candidate chromosome representing the optimal solution, which will be performed as the optimized function. This detail will be presented in the following section. The flowchart of the proposed algorithm is demonstrated in Figure 2. The algorithm performs repeatedly until the maximum number of generations has been reached.

### 3.2. Fitness Function

The main purpose of this paper is to form equal groups of students. Hence, it is important to determine whether the amount of variance within each group is roughly equal and a set of means is similar. Essentially, the comparisons of divided groups of students are required to calculate the F-test in ANOVA. Therefore, an ANOVA-fitness function is designed to guide the algorithm for searching the best solution in forming homogeneous student groups. ANOVA is a statistical model that, theoretically, contrasts the means of various experimental data. It is employed to examine the characteristics of each feature set in order to test the null hypothesis that the means of several populations are equal [22]. Additionally, ANOVA measures two size of variations, the relative size of variance among group means (between group variance) and the average variance within groups (within group variance) [23], for computing the F-test presented in

(2). It is a static ration to test of equality of means under the assumption of normal populations and homogeneous variances.

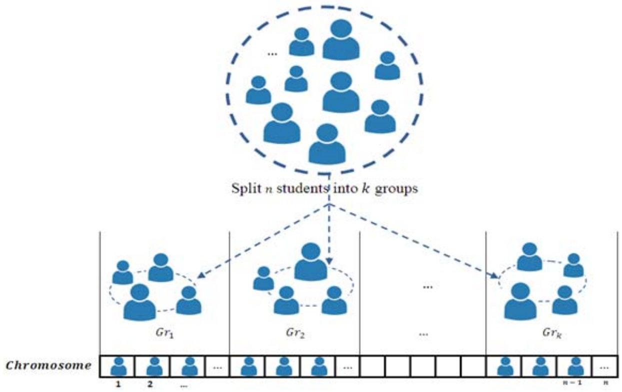


*Figure 1. Chromosome structure for forming student of n students, where k is the number of groups*

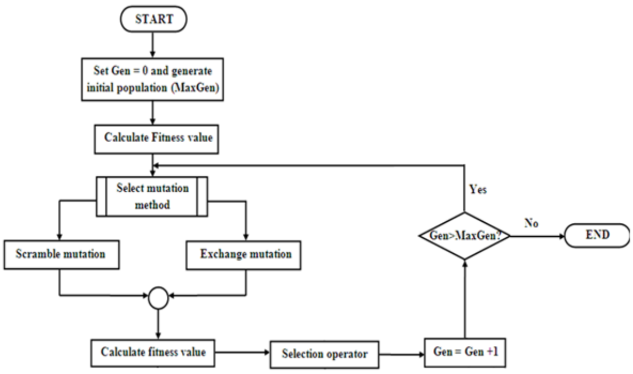


*Figure 2. Flowchart of the algorithm*

If the Between-group variation is greater than the Within-group variation, the F-statistic will be greater. Thus, the larger the F-test implies that the group means greatly different from one another in comparison to the variation in individual observations in each group means.

The F-test, on the other hand, will be very low if the Between-group variation is very low compared to the Within-group variation. If the F-test ratio is close to zero, it truly indicates that all groups are truly similar at the population level.

$$F = \frac{\text{Between−group variance}}{\text{Within−group variance}}. \quad (2)$$

**Between-group variation** ($SS_{between}$) is the total variation between each group mean and the overall mean given by

$$SS_{between} = \sum_{i=1}^{k} n_i(\bar{x}_i - \bar{\bar{x}}_i)^2 \quad (3),$$

where $k$ is the number of groups,
$n_i$ is the size of group $i$,
$\bar{x}_i$ is the mean of group $i$,
$\bar{\bar{x}}_i$ is the mean of all data.

This equation is called the sum of squares between groups, or $SS(B)$. In addition, it is important to note if the group means do not differ greatly from each other and the grand mean, the value of $SS_{between}$ will be small. For $k$ groups of students, the degrees of freedom will be $k-1$. Therefore, mean square the between group variation ($MS_{between}$) will be divided by its degrees of freedom represented in (4).

$$\text{MS}_{\text{between}} = \frac{\text{SS}_{\text{between}}}{\text{k}-1} \quad (4)$$

**Within-group variation** ($SS_{within}$) refers to variations caused by differences within the same group and this is the unexplained variation. Hence, for each element of data, it is calculated by the difference between that value and the mean of its group illustrated in (5).

$$SS_{within} = \sum_{j=1}^{k} \sum_{i=1}^{n_i} (x_{ij} - \bar{x}_j)^2. \quad (5),$$

where $k$ is the number of groups.
$n_i$ is the size for group $i$.
$x_{ij}$ is the data in group $g$.

As there are $k$ number of groups, the total degrees of freedom of within-group variation is $k$ less than the total number of all data, $n-k$. Therefore, mean square of the within group variation ($MS_{within}$) will be divided by its degrees of freedom represented in (6).

$$MS_{within} = \frac{SS_{within}}{n-k}. \quad (6)$$

Figure 3 illustrates the idea of how a chromosome can be used to calculate its fitness value. Obviously, if all groups are truly different due to the difference mean of all groups, between-group variance will be greater than within-group variance. Then, the F-test ratio in (2) is big. On the other hand, if the F-test ratio is sufficiently small, we can conclude that all groups have the same mean and variance. As mentioned previously, the proposed algorithm employs the F-test in ANOVA to determine whether the variability between group means is smaller than the variability of the observations within the groups. For a given optimization, fitness functions are used for genetic algorithms to search towards optimal solutions. Importantly, we want to form groups of students having the low value of the F-test ratio. Thus, in this paper we need the minimum value of the F-test ratio. In addition, F-test ration in ANOVA has a minimum value of near zero. This basically means that all formed groups are more homogeneous.

Let S be the search space of the group formation problem. Therefore, the optimized solution named $s^*$ is a member in S that is $s^* \in S$. Hence, the optimum solution of our problem defined in (7) if $F\_test(s^*) \leq F\_test(s)$ for all $s \in S$. For each generation, GANOVA needs to search for some chromosomes, which will give the lowest F-test ratio among others.

$$Mininmize\left(F\_test(s) = \frac{Between-group\ variance}{Within-group\ variance}\right) \quad (7)$$

subject to s∈S.

The algorithm works repeatedly as presented in Figure 2 until the number of generations is greater than the predefined maximum number of generations. In the last generation, the chromosome with the minimal F-test fitness value is the optimum solution for the problem.

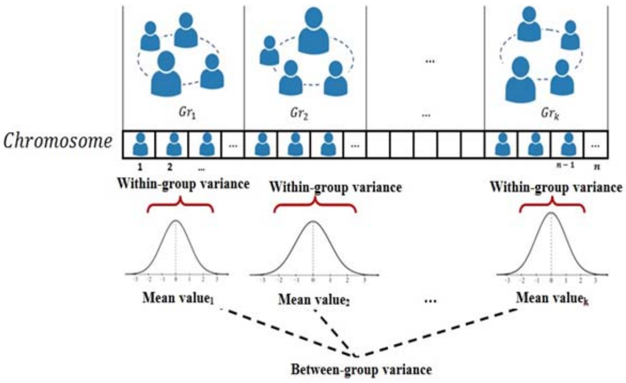


*Figure 3. Representation of how a chromosome can be used to calculate its ANOVA-fitness value for GANOVA algorithm*

The following subsection will go over the selection and mutation operators. Essentially, selection operators will select chromosomes with a low F-test value for the next generation, resulting in a more homogeneous grouping in the following generation. The mutation is frequently used to generate new solutions in the hope of finding a better solution by making minor changes to existing parents. It will randomly change parts of the parents to find offspring with the lowest F value.

### 3.3. Selection Operator

The selection operator is an important operator guiding the evolution of a GA in which chromosomes of a current population are chosen for later breeding. In this paper, the steady state selection is employed by selecting a few good chromosomes for creating new offspring in each generation. As the steady state selection keeps the population size constant, bad chromosomes of the current population will not be allowed to reproduce for a new offspring. By selecting chromosomes of higher fitness value, multiple copies of good chromosome can then be replaced in the next population.

### 3.4. Mutation Operator

Importantly, the crossover operator must be avoided in our approach based on the specified chromosomal representation of the problem.

This is because the crossover operator may produce an unqualified offspring in which some students belong to several groups while others do not. For that reason, the crossover operator is omitted in the algorithm. Scramble mutation and exchange mutation are employed in the proposed algorithm to produce offspring for each generation.

### 3.5. Scramble Mutation Operator

The scramble mutation operator is an operator that helps guide GAs towards the optimized solution to our problem. In addition, the purpose of this operator is to increase genetic diversity by changing the genes of the offspring. A randomly selected portion of the chosen chromosome and its value of genes are scrambled or shuffled randomly. Suppose we have a set of nine students, $S = \{s_1, s_2, s_3 \dots, s_9\}$, which are required to equally divide into 3 groups. For example, a random chromosome encoding three groups, which are $Gr_1 = \{s_5, s_6, s_9\}, Gr_2 = \{s_1, s_3, s_8\}$ and $Gr_3 = \{s_2, s_4, s_7\}$, is presented in Figure 4. And, suppose two random points are 3 and 7. We can then scramble or shuffle the genes which are located between them randomly to make offspring. As we can see, some parts of the offspring are the same as the parent. However, the offspring presents a new group formation, where $Gr_1 = \{s_5, s_6, s_8\}, Gr_2 = \{s_1, s_2, s_9\}$ and $Gr_3 = \{s_3, s_4, s_7\}$ respectively.

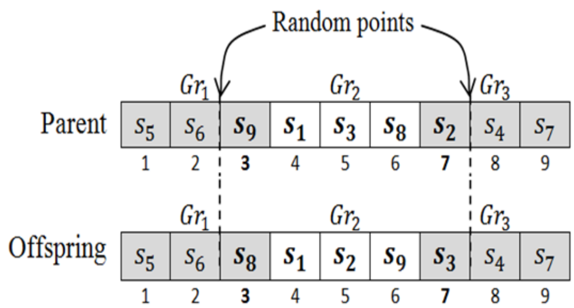


*Figure 4. An example of the scramble mutation operator*

### 3.6. Exchange Mutation

The exchange mutation is also important for our GAs as it is used to increase genetic diversity from one generation to the next. In this mutation, it randomly selects a chromosome as a parent. Two points of the chromosome are selected randomly and then exchanged between each other. Therefore, an offspring is similar to its parent except only two points are swapped. An example of exchange mutation is illustrated in Figure 5. Let the parent chromosome encode the group formation of $Gr_1 = \{s_5, s_6, s_9\}, Gr_2 = \{s_1, s_3, s_8\}$ and $Gr_3 = \{s_2, s_4, s_7\}$ and the random points are 1 and 6.

The exchange mutation creates the offspring of a new group formation, where $Gr_1 = \{s_8, s_6, s_9\}, Gr_2 = \{s_1, s_3, s_5\}$ and $Gr_3 = \{s_2, s_4, s_7\}$.

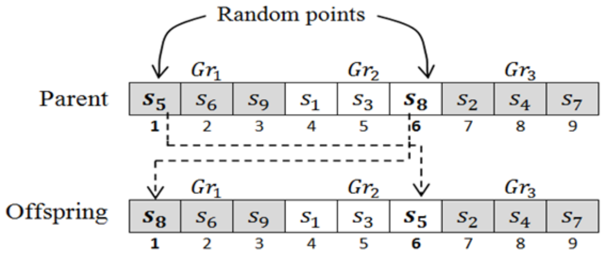


*Figure 5. An example of the exchange mutation operator*

## 4. Experimental Result and Discussion

The algorithm proposed in this paper is implemented by C++ programming language on a PC with Intel(R) Core (TM) i7 @2.93 GHz processor (8GB of RAM). For all experiments, genetic parameter values are given in the Table 1. Three datasets with varying degrees of complexity were employed for the simulation in order to measure the effectiveness of the GANOVA algorithm. We provide three types of datasets as input parameters to demonstrate that the proposed algorithm can be run on a large data set. In addition, datasets with different numbers of students were generated randomly as presented in Table 2. The number of students who participate in these datasets ranges from 10 to 100. we increase the number of learning-style groups in the other datasets to demonstrate the algorithm's efficiency.

Because genetic algorithms are metaheuristic, there is no general analysis that can be applied to all genetic algorithms. In this work, we use the terms "convergence time," the efficiency of the algorithm. Furthermore, the time complexity for determining the smallish status of the F-test to create equal groups of students while assuring the required parameters is proportional to the size of the solution. The time complexity in this work is determined experimentally by the initial population size and maximum generation (Table 1). The convergence time is also affected by the size of the solutions, which is relevant to the number of students and needed attributes for group formation. As a result, we discovered that the first data set ran the quickest, while the third data set ran the slowest during the experiment.

The number of groups to be generated varies from 3 to 20. The results obtained by the proposed algorithm are verified by ANOVA illustrated in Table 3-Table 5. In our experiment, the statistical significance level was set as $\alpha = 0.05$. Additionally, we arbitrarily employed the score of VAK learning style, which was developed by Barbe et al. [24] in 1988.

It helps dividing students in accordance with their preferences into three learning-styles groups, which are the Visual (V), Auditory (A), and the Kinesthetic (K) sensory modalities.

*Table 1. GANOVA's parameters for controlling three datasets*

| Parameters | Types and Range |
|---|---|
| Initial population size | 500 |
| Maximum generation | 100-1000 |
| Mutation operators | a) Scramble mutation operator<br>b) Exchange mutation |
| Selection operator | Steady state selection |

*Table 2. Descriptions of each dataset*

| Dataset | Number of students (n) | Number of divided groups | Number of attributes |
|---|---|---|---|
| 1 | 10 | 3 | 1 |
| 2 | 25 | 5 | 2 |
| 3 | 100 | 20 | 3 |

**Dataset 1:**

As dataset 1 uses only one attribute for generating homogeneous groups by the algorithm, the obtained result presenting in Table 3 is one-way ANOVA. The hypotheses of conducting a one-way ANOVA for dataset 1 are as follows:

$H_0$: $\mu_1 = \mu_2 = \mu_3$

$H_1$: Means are not all equal

, where $\mu_k$ is the mean value for group $k$ and $1 \leq k \leq 3$.

In ANOVA, the null hypothesis is that all groups have no difference in means. If $\alpha = 0.05$ level of significance, the $F_{0.95,2,7} = 4.75$. Obviously, the algorithm generates groups from dataset #1 with F = 0.000, which indicates that the proposed algorithm is able to create homogeneous groups with the same mean, see Figure 6 for detail.

*Table 3. ANOVA's result obtained from dataset #1*

| Score | Sum of Squares | df | Mean Square | F |
|---|---|---|---|---|
| Between Groups | .000 | 2 | .000 | .000 |
| Within Groups | 1648.000 | 7 | 235.429 | |
| Total | 1648.000 | 9 | | |

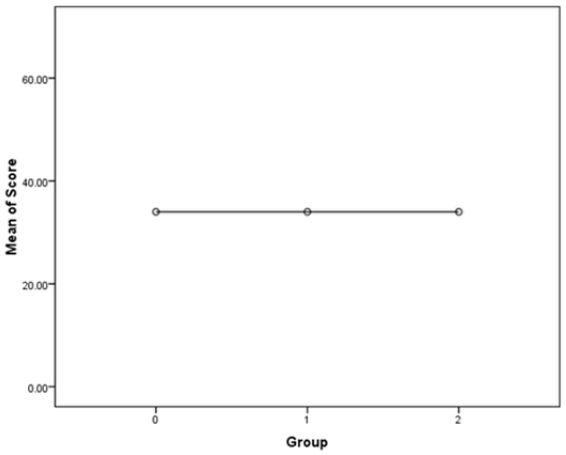


*Figure 6. ANOVA's result obtained from dataset #1*

**Dataset 2:**

This dataset has 25 students, which will be divided into five groups. As two attributes are used to generate homogeneous groups, two-way ANOVA is used to analyze the experimental results obtained from the algorithm. However, in this experiment, we used only modality V and A for learning styles as the main factors for the algorithm to search for optimal groups of students. The analysis in two-way ANOVA with a 5% level of significance are generated by SPSS and illustrated in Table 4. In the experiment, we determine whether there is an interaction between the learning styles and divided groups. Hence, the hypotheses of conducting a two-way ANOVA for dataset 2 are as follows:

$H_0$: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$
$H_1$: Means are not all equal,

where $\mu_k$ is the mean value for group $k$.

As can be seen in the Table 4, the F-test ratio of the interaction between Group and LearningStyles (Group*LearningStyles) is zero. Additionally, the p value for the interaction between Group and LearningStyles is equal to 1.000. It implies that we retain $H_0$, meaning that our algorithm forms the homogeneous groups equally. It can be observed in Figure 7 that the mean value of both V and A of five generated groups are similar. That is, we can conclude that the proposed algorithm can create homogeneous groups for this dataset as well.

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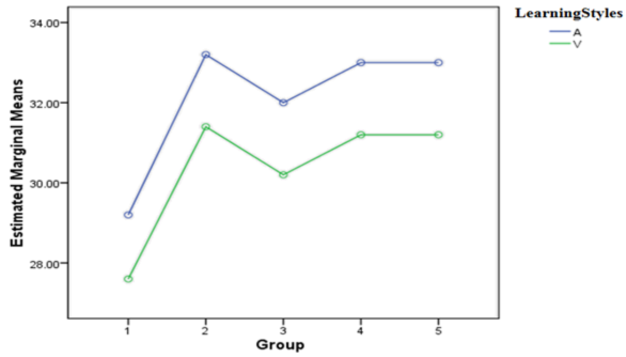



*Figure 7. Mean of V and A of groups for dataset 2*

**Dataset 3:**

In this dataset, 100 students are divided into 20 equal groups. Hence, each group consists of 5 students. All types of learning styles, which are V, A and K, are employed to generate homogeneous groups; therefore, two-way ANOVA is used to analyze the experimental results obtained from the algorithm. Then, we analyze generated groups in two-way ANOVA by SPSS demonstrated in Table 5. The hypotheses of conducting a two-way ANOVA for dataset 3 are as follows:

$H_0$: $\mu_1 = \mu_2 = \mu_3 = \ldots \mu_{19} = \mu_{20}$
$H_1$: Means are not all equal,

where $\mu_k$ is the mean value for group $k$ and $1 \leq k \leq 20$.

Looking at the F-test ratio of the interaction between Group and Learning Styles (Group*Learning Styles) tells us that we can accept our null hypothesis. This is because the F-test ratio is equal to zero. It indicates that the algorithm is able to generate the homogeneous groups, in which the mean value of all factors (V, A and K) using for this experiment are similar to those presented in Figure 8. Moreover, for this dataset, the homogeneity of variances is tested using Levene's test for equality of variances demonstrated in Table 6. This is incorporated into the basic technique for performing the two-way ANOVA, allowing us to assess the homogeneity of variances concurrently with receiving the two-way ANOVA results with a 5% level of significance. Obviously, the Sig. = 0.319 is greater than the significance level of 0.05. That is, the variance of all attributes across generated groups is significantly equal. Hence, the proposed algorithm can obtain an optimum result, as we have the homogeneity of variances of the dependent variable across generated groups.

*Table 4. ANOVA's result[a] obtained from dataset #2*

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 145.600[a] | 9 | 16.178 | .050 | 1.000 |
| Intercept | 48672.000 | 1 | 48672.000 | 149.067 | .000 |
| Group | 106.800 | 4 | 26.700 | .082 | .988 |
| LearningStyles | 38.720 | 1 | 38.720 | .119 | .732 |
| Group * LearningStyles | .080 | 4 | .020 | .000 | 1.000 |
| Error | 13060.400 | 40 | 326.510 | | |
| Total | 61878.000 | 50 | | | |
| Corrected Total | 13206.000 | 49 | | | |

*a. R Squared = .011 (Adjusted R Squared = -.211)*

*Table 5.* ANOVA's result[a] obtained from dataset #3

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 1175.530[a] | 59 | 19.924 | .053 | 1.000 |
| Intercept | 154995.870 | 1 | 154995.870 | 412.691 | .000 |
| Group | 1118.863 | 19 | 58.888 | .157 | 1.000 |
| LearningStyles | 53.060 | 2 | 26.530 | .071 | .932 |
| Group * LearningStyles | 3.607 | 38 | .095 | .000 | 1.000 |
| Error | 90137.600 | 240 | 375.573 | | |
| Total | 246309.000 | 300 | | | |
| Corrected Total | 91313.130 | 299 | | | |

*R Squared = .013 (Adjusted R Squared = -.230)*

*Table 6. Levene's Test of Equality of Error Variances[a]*

| F | df1 | df2 | Sig. |
|---|---|---|---|
| 1.091 | 59 | 240 | .319 |

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Group + LearningStyles + Group * LearningStyles

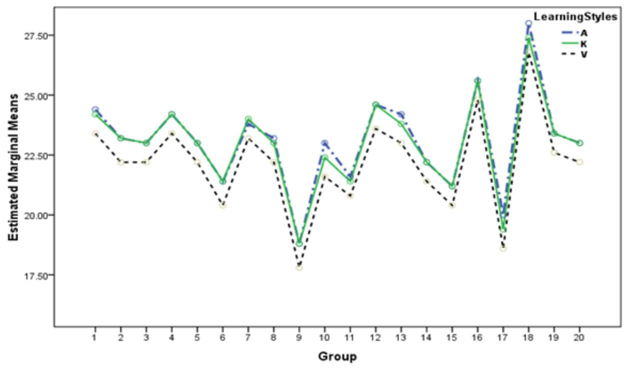
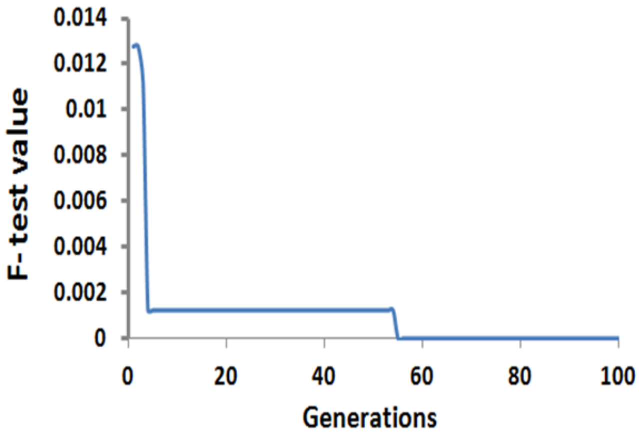
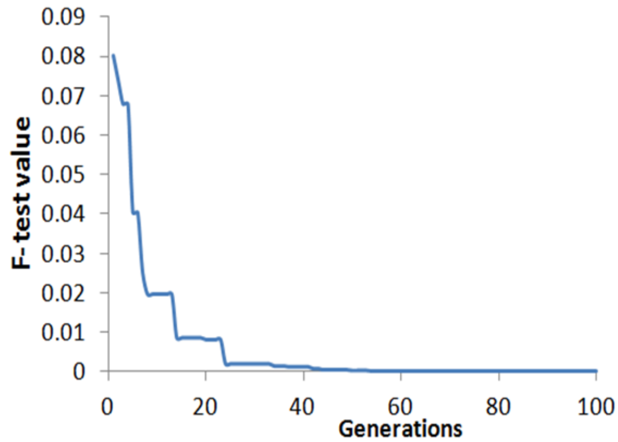



*Figure 8. Mean of groups for dataset 3*

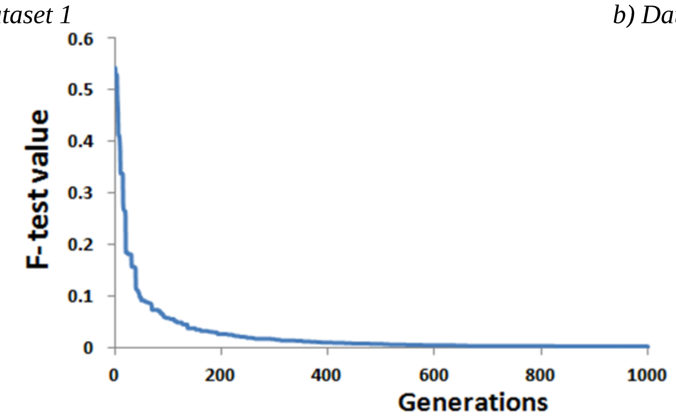
Experimental results presented above indicate that the proposed algorithm performs well as it can yield optimal solutions in terms of an F-test ratio, a fitness value of the algorithm. Additionally, the following figures presented in Figure 9 are the graphical results obtained by the proposed algorithm and they illustrate that fast convergence of all optimal solutions can be obtained. As the number of students for both dataset 1 and dataset 2 is small, the space of all feasible solutions became small as well. Hence, the optimal solution of both datasets can be quickly found. The algorithm runs until it is convergent to get the optimum result, which takes about 100 generations. As can be observed in both Figure 9(a) and Figure 9(b) that the algorithm rapidly moves toward to the optimal solution in a few generations. During the execution, we discovered that the first data set has the shortest convergent time because it has the fewest students and attributes.




*a) Dataset 1*




*b) Dataset 2*




*c) Dataset 3*

*Figure 9. Examples of the GANOVA algorithm's results that demonstrate how every optimal solution can rapidly converge*

On the other hand, the third data set has the longest convergent time because it contains more students and attributes. Figure 9(c) illustrates the result obtained from the algorithm for the last dataset. One hundred students were separated into 20 groups of 5 students each. Hence, the search space of the student formation problem becomes big. As the result shows, the algorithm takes a longer time to search for the optimum results. The F-test value gradually moves to zero when the number of generations is approximately 500.

## 5. Conclusions and Future Work

We have proposed a GA-based algorithm to search for best possible groupings of students, where each established group contains individuals with similar educational learning styles. To accomplish this objective, the ANOVA F-test is incorporated into the fitness function to ensure that the algorithm is able to search for the solution, where variance values for generated groups are equal. Additionally, to measure the performance of the proposed algorithm, empirical experiments were developed by simulation datasets of varying numbers of students and different numbers of specific student characteristics. According to our empirical experiments, the results have been proven to show that the proposed algorithm performed effectively for forming optimally homogeneous groups of students, as the F-test of equality of variances for established groups is near zero. For future research, we shall continue to examine the robustness of the algorithm for larger datasets to support collaborative learning in the university. Additionally, the algorithm will be compared to other meta-heuristic optimization algorithms and traditional methods in different aspects, such as student satisfaction with the learning experience, group grades and individual grades. More importantly, we will integrate to optimize the mathematical model in additional constraints to precise the running time, while providing an optimal group number and composition. Furthermore, more effective similarity measures of variations should be investigated in future studies to provide better learning results.

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