Genetic Algorithms for Optimizing Grouping of Students Classmates in Engineering Education

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***Abstract*—In this research article, we propose a method based on genetic algorithms to optimize the grouping of students in engineering education. Our method aims to create student groups that take into account their skills, preferences, and relevant factors. We build upon previous research that has successfully utilized genetic algorithms for group formation in various contexts, such as assigning students to laboratory groups and facilitating cooperative learning. We implement and evaluate our proposed methods in collaborative learning environment, examining their impact on collaborative performance, processes, and perceptions. The results of our research demonstrate that grouping methods supported by genetic algorithms positively influence performance and collaborative processes, while students perceive these methods as fair and effective. This article makes a valuable contribution to the field of engineering education by providing methods that up to minus student grouping, considering their initial characteristic and performance and preferences. By employing these methods, the quality of group work can be enhanced leading to improve student learning experiences. Future research can explore the application of the of this method in order educational settings and investigate the factors that influence their effectiveness.**

***Index Terms*—Class grouping, optimization, genetic algorithm**

I. Introduction

The classification of learning classes in engineering education using information technology has emerged as a prominent trend in education over the past few decades [1]. Various techniques have been employed, including data mining [2], genetic algorithms [3], fuzzy algorithms [4, 5], k-means clustering algorithm [6], and learning grouping strategies based on the K-means clustering algorithm tailored to students' learning styles [7].

Class grouping plays a vital role in enhancing learning [8, 9], assisting teachers in choosing suitable strategies and methods [10], and maximizing academic achievement [11–15]. Furthermore, beyond individual traits, classmates also exert influence on student grouping [16], as peers contribute to character development [17] and motivation to learn [18]. Hence, the grouping of student should consider the diverse composition of characteristics within each class [19].

There are two types of learning class grouping: homogeneous grouping based on specific criteria, and heterogeneous grouping that combines multiple criteria [20, 21]. Heterogeneous grouping offers several benefits: (1) it provides opportunities for mutual teaching and support among students [22], (2) enhances relationships and interactions across diverse racial, religious, ethnic, and gender backgrounds [23], and (3) facilitates effective classroom management [24]. However, student grouping is influenced by various constraints arising from differences in student characteristics, including gender, regional origin, school background, academic performance, religion, and parental socioeconomic status [25].

The classification of learning classes in Engineering Education, particularly in Informatics Engineering Education, holds significant importance due to the diverse backgrounds of students entering the program, not all of whom come from high schools with a focus on informatics disciplines [26]. Analyzing the data from the 2019 intake of Informatics Engineering Education at Padang State University, it was found that out of the total students, 11 came from vocational high schools specializing in Information Technology, with programs such as Computer Network Engineering, Software Engineering, and Multimedia. Additionally, 64 students joined from regular high schools, while 11 students came from Senior High School. In the Computer Network Practicum course, it was observed that the learning outcomes of the F1 class (students with a background in Computer and Network Engineering) were higher compared to those of the F2 class. The F1 class demonstrated superior and faster learning progress due to their foundational knowledge in Computer and Network Engineering [27, 28]. Consequently, the F2 class slightly lagged behind in terms of material coverage. This discrepancy also resulted in lower student interest in the F2 class, as some students from the Computer and Network Engineering department felt bored due to the repetition of previously covered material.

The study of genetic algorithms has incorporated constructivist learning theory, employing a direct learning strategy that contextualizes the learning experience and enables students to experiment with algorithms [29]. This approach aligns with the principles of constructivism, which highlight the significance of context and adaptation in the learning process [30]. Constructivism is a learning theory that underscores the active role of learners in constructing their own understanding. It posits that learners develop new meaning and understanding by reflecting on their experiences and creating mental representations [31–34].

This paper aims to establish an inter-homogeneous and intra-heterogeneous learning class through an alternative grouping approach that utilizes genetic algorithms to optimize the distribution of learning classes [35–37]. Genetic

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algorithms serve as effective heuristic search methods that seek satisfactory solutions with reduced computational requirements [38–40]. The grouping process within the genetic algorithm begins by forming an initial population consisting of student data with multiple criteria, with each individual assigned a fitness value [41]. Individuals with higher fitness scores are more likely to be selected and reproduced, while those with lower fitness scores are more likely to be excluded from the population, as the fitness value serves as a measure of chromosomal compatibility [42]. Following fitness formation, a cross-hover process takes place between individuals, followed by mutation [43]. Through this mutation process, group formation starts to emerge [44]. Furthermore, the selection process for individuals in this stage is based on the highest fitness value [36]. Ultimately, the best individual is identified, representing the outcome of the study group report [33, 45, 46].

This study aims to develop an optimal design for the formation of learning classes, aiming to achieve optimal learning outcomes through effective and efficient arrangements. The primary objectives include enhancing academic achievement, promoting student participation and engagement, fostering diversity and inclusiveness within groups, facilitating positive social interactions, considering individual needs, improving learning efficiency and effectiveness, and increasing student satisfaction. It is important to note that these objectives may vary depending on the context and characteristics of the students. To successfully achieve these goals, a thorough understanding of the students, teaching methods, and learning objectives is essential.

II. Method

A. Data Set

In this study, we will employ cluster sampling by randomly selecting one study program and considering the entire population of students from that program as the sample. The population under consideration comprises the 2019 cohort of the Computer Engineering Education Study Program, located within the Department of Electronics Engineering, Faculty of Engineering, at Universitas Negeri Padang, with a total of 114 students.

Drawing from the available data, the research variables will be determined based on established criteria. Table I presents the following standards that will be utilized for classifying students:

TABLE I: Criteria for Students' Description

Criteria	Sub-Criteria	Score
Entrance (JM)	SNMPTN SBMPTN Independent	SNMPTN = 1 SBMPTN = 2 Independent = 3
the origin of the school (AS)	SMA/MA SMK	SMA/MA = 1 SMK = 2
Gender (JK)	Female (P) Male (L)	P = 1 L = 2
IPA value (NIPA)	Average IPA	Average IPA
IPS score (NIPS)	Average IPS score	Average IPS score
Language score (NB)	Average Language Score	Average Language Score
math score (NM)	Average Maths scores	Average Maths scores
GPA (point average)	The average value of the last grade	The average value of the last grade
hometown (ADVERTISEMENT)	1. In the city of Padang	1
	2. Outside the City of Padang but West Sumatra Province	2
	3. Outside West Sumatra Province	3
Religion (AG)	1. Islam	1
	2. Protestant	2
	3. Catholic	3
	4. Hindu	4
	5. Buddha	5
	6. Confucius	6
Parent's income (PO)	1. < Rp. 750,000	1
	2. Rp. 750,001–Rp. 1,000,000	2
	3. Rp. 1,000,001–Rp. 2,500,000	3
	4. Rp. 2,500,001–Rp. 4,500,000	4
	5. Rp. 4,500,001–Rp. 5,500,000	5
	6. > Rp. 5,500,001	6

Notes: The abbreviations in this table are used to perform genetic algorithm analysis in the formation of study groups.
- Entrance is abbreviated as JM (admission pathway), where:
  - SNMPTN is the National Entrance Examination for State Universities (based on student achievement)
  - SBMPTN is the National Entrance Examination for State Universities
  - Independent is an independent or regular path to enter a collage
  - The origin of the school is abbreviated as AS, where:
    - SMA is SMA, MA is Islamic High School
    - SMK is a Vocational High School
- Gender is abbreviated as JK where male 'L' and female 'P'.
- IPA value (Natural Sciences) is abbreviated as NIPA
- IPS score (Social Sciences) is abbreviated as NIPS
- Language score is abbreviated as NB
- Math score is abbreviated as NM
- GPA (cumulative grade point average) is abbreviated as IPK
- Hometown is abbreviated as AD
- Religion is abbreviated as AG
- Parent's income is abbreviated as PO

B. Genetic Algorithm

Charles Darwin identified genetic algorithms as one of the effective algorithms for addressing optimization and search challenges based on a given function [47–51]. This algorithm operates by generating a population of potential solutions (individuals) and iteratively evolving them across generations to discover improved solutions. Each individual in the population represents a potential solution, encoded as a set of parameters or 'genes' [45, 49].

Genetic algorithms have found applications in diverse domains such as engineering, computer science, economics, and biology. They offer a flexible and powerful approach to tackle complex problems by drawing inspiration from the principles of natural evolution and genetics [42].

A recent study by Moreno *et al.* [36] employed a genetic algorithm to optimize student clustering across five different classes. The objective of the research was to create well-balanced student groups based on academic performance and other relevant characteristics. The genetic algorithm was utilized to generate group partitions by redistributing students among different groups through a three-step iteration process. The fitness function employed in the genetic algorithm was ANOVA, a statistical method used for comparing means between groups. The study compared the results obtained from the genetic algorithm with two other approaches: random student clustering and an alternative algorithm based on the work of Konert *et al.* [52]. The findings demonstrated that the genetic algorithm outperformed the other approaches in forming well-balanced student groups based on academic performance. These results highlight the effectiveness of genetic algorithms in optimizing student clustering within engineering education. It is noteworthy that various studies in this field have employed different fitness functions and algorithms to develop group partitions and create well-balanced student groups based on diverse characteristics [30, 53, 54].

Distinct from other optimization techniques, genetic algorithms conduct the search process guided by the criteria outlined in Fig. 1 [55]:

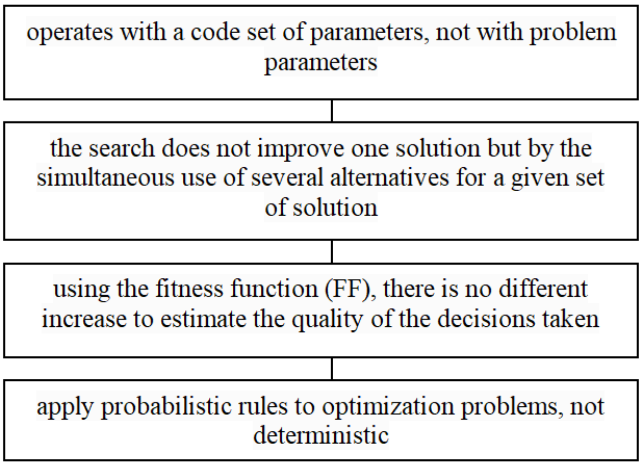

Fig. 1. Genetic algorithm search procedure.

Fig. 2 presents the flowchart of the genetic algorithm as follows:

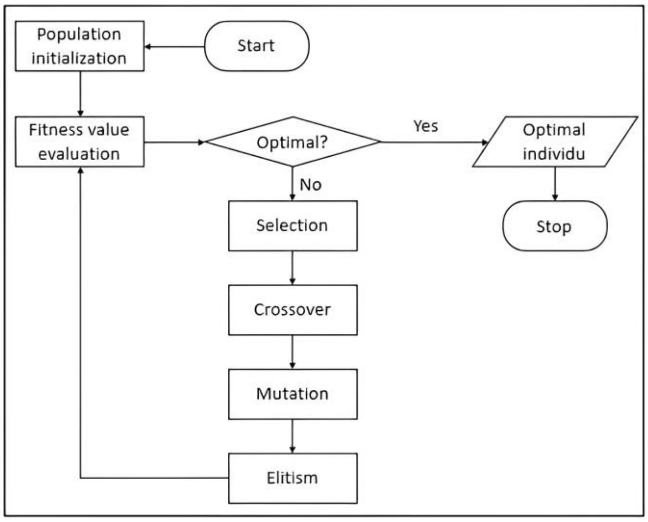

Fig. 2. The genetic algorithm diagram.

In this study, the genetic algorithm utilized involves the determination and setting of several crucial parameters that drive the evolution process. Specifically, within the scope of this research, genetic algorithms are employed to optimize parameters associated with hybrid data-driven fuzzy active disturbance rejection control. These parameters include fuzzy logic parameters, active controller parameters, and other variables that significantly impact the performance of tower crane systems [5]. By employing genetic algorithms for learning clustering, optimal combinations of parameters can be identified based on data collected from real-world tower crane systems. Through adaptive iterations and evolution, genetic algorithms enable the improvement of these parameters, thereby enhancing the control performance of tower crane systems when dealing with disturbances.

Moreover, the utilization of genetic algorithms in this research enables the generation of more efficient and effective learning clustering, resulting in improved system control performance. Genetic algorithms can be employed to enhance control parameters by utilizing feedback acquired from the adaptive learning process, including set-point updating as discussed in the article titled "Enhanced P-type Control: Indirect Adaptive Learning from Set-point Updating," published in the IEEE Transactions on Automated Control [56]. The parameters considered in this context are as follows:

1. Population Size
   The population size is configured to accommodate 100 individuals. This parameter denotes the number of individuals within the population utilized during each generation of the genetic algorithm.
2. Number of Generations
   The number of generations is set to 50, indicating the total number of evolutionary cycles performed by the genetic algorithm until the stopping condition is met.
3. Crossover Probability
   The crossover probability is set to 0.3, determining the likelihood of crossover occurring between two individuals in the population during the genetic recombination process.
4. Mutation Probability
   The mutation probability is set to 0.1, governing the frequency of mutation in individuals within the population during the genetic variation process.
5. Selection Method
   The tournament selection method with a tournament size of 5 is employed. This method facilitates the selection of the most promising individuals from the population during the selection process.
6. Fitness Function
   A fitness function is utilized to assess the gene distribution within each individual in the group formation. This function assigns a numerical score based on the individual's performance, which is used in the evaluation and selection of the fittest individuals.
7. Crossover and Mutation Operators
   The single-point crossover operator and the bit-flip mutation operator are applied. The single-point crossover operator divides the individual's chromosome into two segments and exchanges those segments with another selected individual during crossover. On the other hand, the bit-flip mutation operator alters the bit values within the selected individual's chromosome, introducing genetic variations.

By establishing and defining these parameters, the genetic algorithm can engage in an evolutionary process that leverages the principles of natural selection. Through this process, the algorithm aims to identify an optimal or nearly optimal solution to the problem under investigation.

C. Implementation Steps in Genetic Algorithms

The following outlines the steps involved in applying genetic algorithms to group student learning classes:

1. Generate initial population
   The initial population generation entails creating a set of individuals. This process involves randomly selecting or employing specific procedures for each individual, as illustrated in Fig. 3.

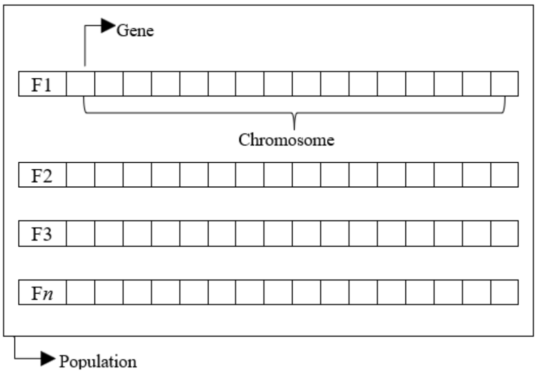

Fig. 3. Gene, chromosome and population design.

Referring to Fig. 3, it is depicted that genes represent the criteria data possessed by students, such as mhs0 [1, 1, 3, 6, 1]. Meanwhile, the chromosome implementation is reflected in the class code, where the number is determined by the length of the chromosome, which in this case is 16 representing the number of students in each class. To determine the number of classes in a large population, the total number of students is divided by 16. The process of formation is elucidated in Fig. 4.

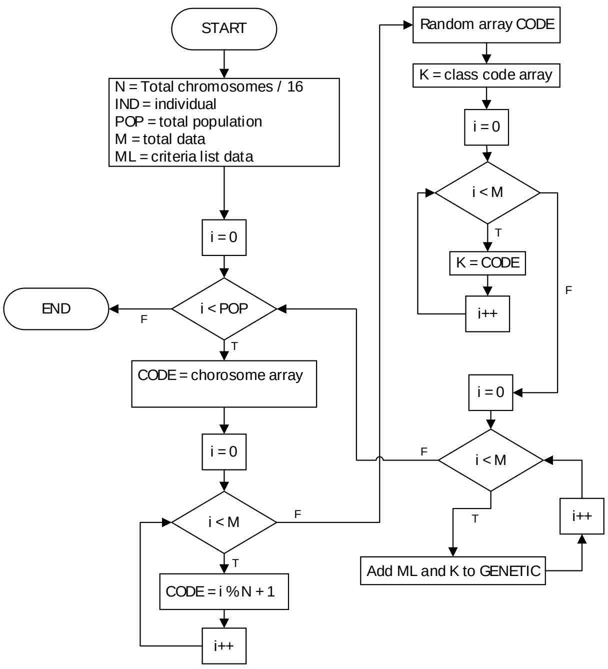

Fig. 4. Flowchart generates population and chromosome encoding.

2. Evaluation
   During this step, each population undergoes evaluation by calculating the fitness value of each chromosome. This evaluation process continues until the desired criteria are met. If the criteria are not satisfied, a new generation will be formed.
3. Fitness value
   The population data, comprising various criteria for each class, is processed to facilitate grouping based on class similarity. The higher the diversity in fitness values, the greater the fitness of the population. The calculation of data heterogeneity per class is illustrated in Fig. 5.

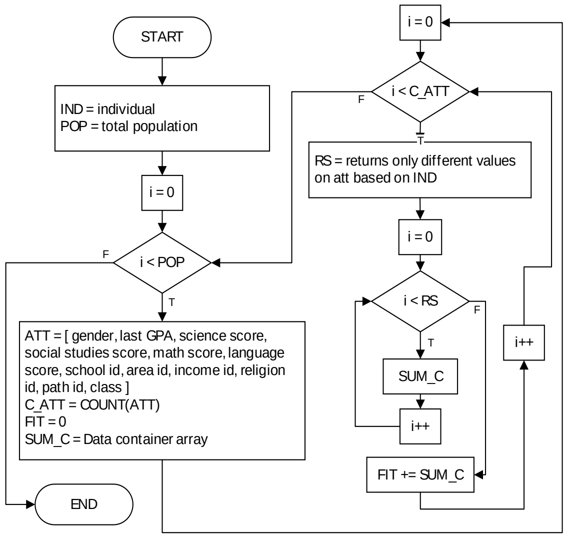

Fig. 5. Flowchart fitness.

4. Crossover
   During the crossover stage, student data is crossed over or exchanged. For instance, if there are 100 individuals, they can be divided into two groups of 50:50 through crossover. The process of crossing over individuals is illustrated in Fig. 6.

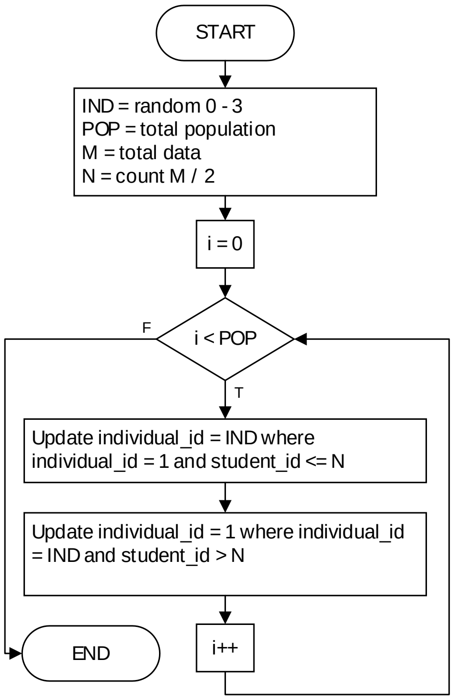

Fig. 6. Flowchart crossover.

5. Mutation
Mutation involves replacing a gene with a new gene, and this process occurs randomly. In the context of class division, the mutation process takes into account a maximum quota limit of 16 people per class. An overview of this mutation process is depicted in Fig. 7.

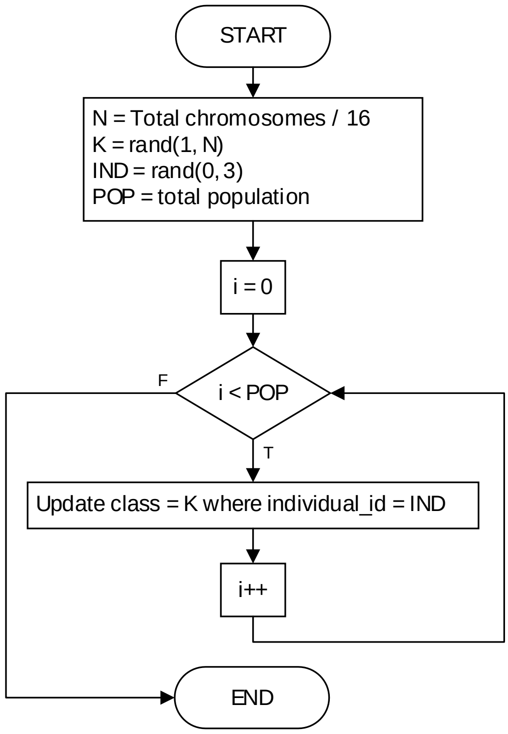

Fig. 7. Flowchart mutation.

6. Selection
The selection process employs the hill climbing method, which involves preserving the individuals with the highest fitness value, as illustrated in Fig. 8.

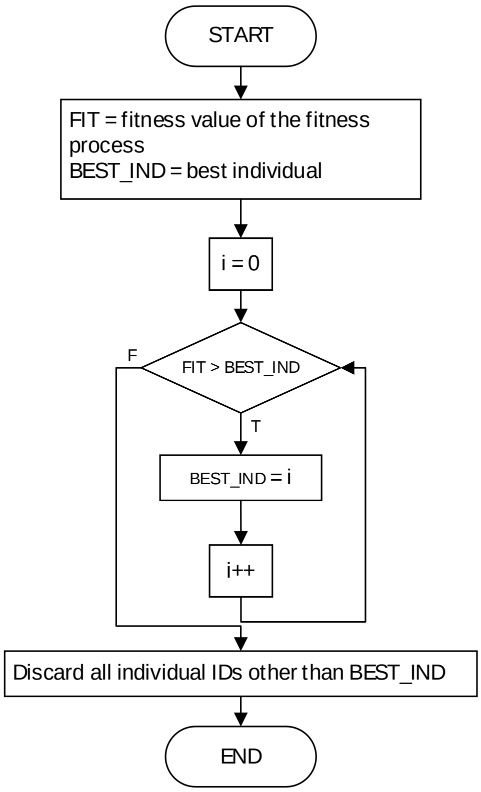

Fig. 8. Flowchart selection.

III. RESULT

The following Fig. 9 presents an overview of the findings derived from the studies conducted in alignment with the operational procedure of the genetic algorithm.

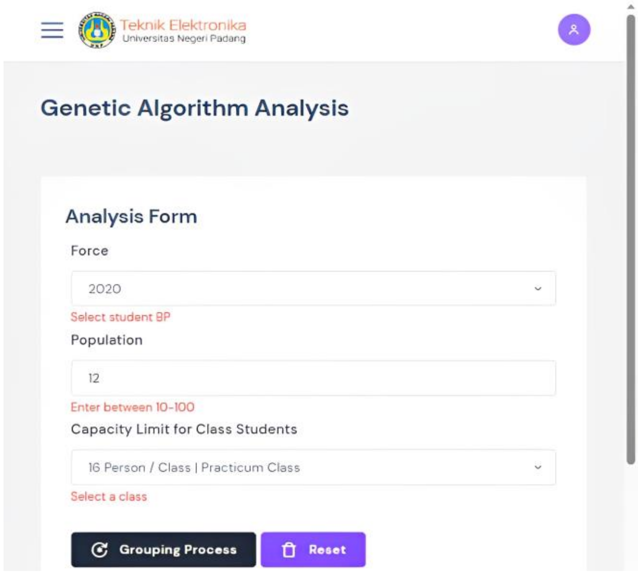

Fig. 9. Genetic's analysis.

Fig. 9 depicts the analytical framework for applying a genetic algorithm in the creation of a learning class. The students selected from the 2020 cohort are divided into 12 populations, with each learning class accommodating up to 16 individuals.

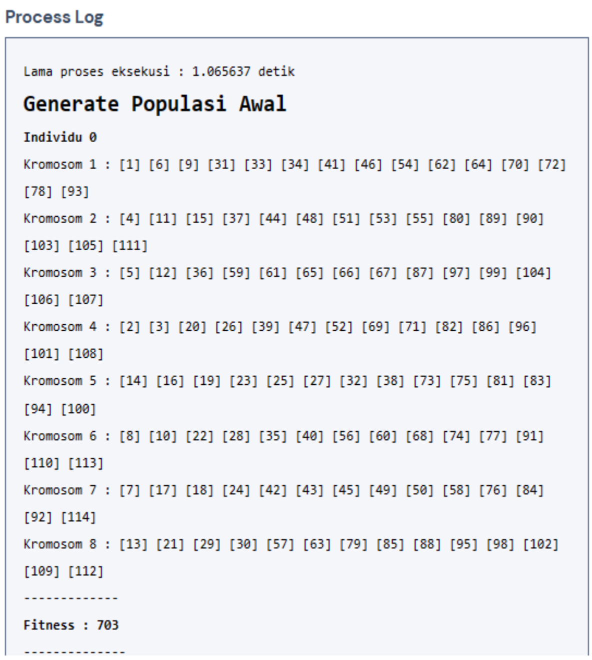

Fig. 10. Process log.

According to Fig. 10, the formation of the initial population takes a few seconds. The results of the initial population initialization can be observed, showing a fitness value of 703. This leads to the creation of eight chromosomes, with each chromosome consisting of 15–16 genes. Consequently, there are eight learning class groups, each containing 15 to 16 students. For more details on the initialization process of this population, please refer to Table II.

TABLE II: RESULTS GENERATE POPULATION AND CHROMOSOME CODING

ID	IND	MHS	JK	IPK	NIPA	NIPS	NM	NB	AS	AD	PO	AG	JM	KL
1	0	1	L	3.51	78	92	81	90	1	3	6	1	1	2
2	0	2	P	3.05	83	85	86	89	1	2	1	1	1	1
3	0	3	L	3.56	83	84	80	79	3	2	2	1	1	2
4	0	4	L	3.12	89	82	91	83	1	3	1	3	1	2
5	0	5	L	3.46	93	80	92	84	2	3	1	1	1	2
6	0	6	L	3.34	84	94	82	93	1	2	1	1	1	1
7	0	7	L	3.45	91	83	84	78	1	2	1	1	1	1
8	0	8	L	3.14	83	89	92	87	1	2	1	1	1	1
9	0	9	L	3.36	82	89	83	85	1	3	1	1	1	2
10	0	10	L	3.22	93	87	83	93	2	3	1	1	1	1
11	0	11	P	3.62	92	93	79	92	2	3	3	1	1	2
12	0	12	P	3.33	92	85	89	82	2	3	1	1	1	2
13	0	13	P	2.97	93	86	91	79	2	2	1	1	1	1
14	0	14	P	3.17	92	82	86	92	1	3	2	1	1	1
15	0	15	P	3.23	93	89	82	83	1	2	2	1	1	2
16	0	16	L	3.48	93	89	82	80	2	1	2	3	1	1
17	0	17	P	3.28	86	82	85	94	1	2	1	1	1	1
18	0	18	P	3.09	88	92	80	92	1	2	1	2	1	2
19	0	19	L	3.14	94	89	84	84	1	3	1	2	1	1

Note: ID: Identity, used in genetic algorithm calculations.
IND abbreviation for "individual".
MHS abbreviation for "mahasiswa" (student).
KL symbol used for group determination in genetic algorithm calculations.
And for other abbreviations, please refer to Table I.

According to Table II, the orange column represents the chromosomes that are used as class codes. The chromosomes are assigned as class codes during the data entry process, where chromosomes with the same class code are considered as one chromosome. To achieve optimal learning classes, crossover and mutation processes are performed, and the outcomes of these processes are presented in Table III and Table IV.

Fig. 11. Crossover results.

Fig. 11 displays the results of crossover analysis, which is the process of genetic recombination between individuals. Crossover helps to avoid premature convergence on suboptimal solutions and enhances the chances of finding the best solution within the population. For further clarification, please refer to Table III.

TABLE III: CROSSOVER RESULTS

ID	IND	MHS	JK	IPK	NIPA	NIPS	NM	NB	AS	AD	PO	AG	JM	KL
1	0	1	L	3.51	78	92	81	90	1	3	6	1	1	2
2	0	2	P	3.05	83	85	86	89	1	2	1	1	1	1
3	0	3	L	3.56	83	84	80	79	3	2	2	1	1	2
4	0	4	L	3.12	89	82	91	83	1	3	1	3	1	2
5	0	5	L	3.46	93	80	92	84	2	3	1	1	1	2
6	0	6	L	3.34	84	94	82	93	1	2	1	1	1	1
7	0	7	L	3.45	91	83	84	78	1	2	1	1	1	1
8	0	8	L	3.14	83	89	92	87	1	2	1	1	1	1
9	0	9	L	3.36	82	89	83	85	1	3	1	1	1	2
10	0	10	L	3.22	93	87	83	93	2	3	1	1	1	1
11	1	11	P	3.62	92	93	79	92	2	3	3	1	1	2
12	1	12	P	3.33	92	85	89	82	2	3	1	1	1	2
13	1	13	P	2.97	93	86	91	79	2	2	1	1	1	1
14	1	14	P	3.17	92	82	86	92	1	3	2	1	1	1
15	1	15	P	3.23	93	89	82	83	1	2	2	1	1	2
16	1	16	L	3.48	93	89	82	80	2	1	2	3	1	1
17	1	17	P	3.28	86	82	85	94	1	2	1	1	1	1
18	1	18	P	3.09	88	92	80	92	1	2	1	2	1	2
19	1	19	L	3.14	94	89	84	84	1	3	1	2	1	1
20	3	20	L	3.30	91	91	82	90	1	2	1	1	1	2
21	3	1	L	3.51	78	92	81	90	1	3	6	1	1	2
22	3	2	P	3.05	83	85	86	89	1	2	1	1	1	1
23	3	3	L	3.56	83	84	80	79	3	2	2	1	1	2
24	3	4	L	3.12	89	82	91	83	1	3	1	3	1	2
25	3	5	L	3.46	93	80	92	84	2	3	1	1	1	2
26	3	6	L	3.34	84	94	82	93	1	2	1	1	1	1
27	3	7	L	3.45	91	83	84	78	1	2	1	1	1	1
28	3	8	L	3.14	83	89	92	87	1	2	1	1	1	1
29	3	9	L	3.36	82	89	83	85	1	3	1	1	1	2
30	3	10	L	3.22	93	87	83	93	2	3	1	1	1	1

In Table III, the crossing process between individuals is illustrated, where the green IND is crossed with the orange IND.

TABLE IV: MUTATION RESULTS

ID	IND	MHS	JK	IPK	NIPA	NIPS	NM	NB	AS	AD	PO	AG	JM	KL
1	0	1	L	3.51	78	92	81	90	1	3	6	1	1	2
2	0	2	P	3.05	83	85	86	89	1	2	1	1	1	1
3	0	3	L	3.56	83	84	80	79	3	2	2	1	1	2
4	0	4	L	3.12	89	82	91	83	1	3	1	3	1	2
5	0	5	L	3.46	93	80	92	84	2	3	1	1	1	2
6	0	6	L	3.34	84	94	82	93	1	2	1	1	1	1
7	0	7	L	3.45	91	83	84	78	1	2	1	1	1	1
8	0	8	L	3.14	83	89	92	87	1	2	1	1	1	1
9	0	9	L	3.36	82	89	83	85	1	3	1	1	1	2
10	0	10	L	3.22	93	87	83	93	2	3	1	1	1	1
11	1	11	P	3.62	92	93	79	92	2	3	3	1	1	2
12	1	12	P	3.33	92	85	89	82	2	3	1	1	1	2
13	1	13	P	2.97	93	86	91	79	2	2	1	1	1	1
14	1	14	P	3.17	92	82	86	92	1	3	2	1	1	1
15	1	15	P	3.23	93	89	82	83	1	2	2	1	1	2
16	0	16	L	3.48	93	89	82	80	2	1	2	3	1	1
17	0	17	P	3.28	86	82	85	94	1	2	1	1	1	1
18	0	18	P	3.09	88	92	80	92	1	2	1	2	1	2
19	0	19	L	3.14	94	89	84	84	1	3	1	2	1	1

After evaluating and selecting individuals, the results of grouping student learning classes are obtained, as shown in Fig. 12.

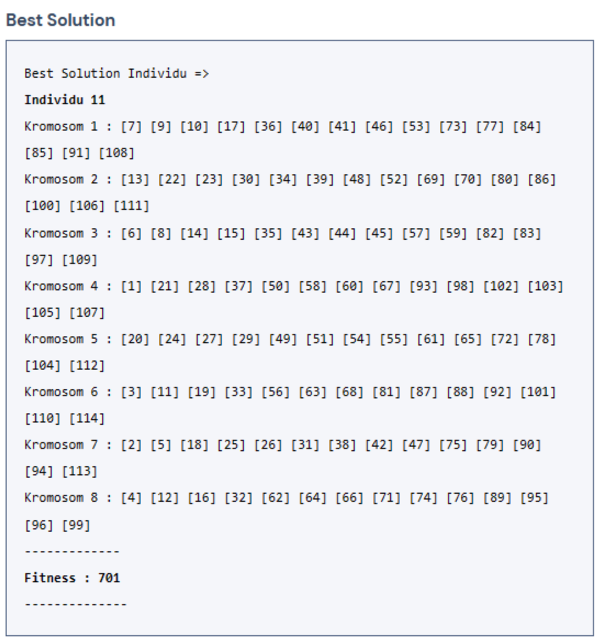

Fig. 12. Best solution.

For more details, the results of the formation of learning class groups can be seen in Table V.

As shown in Table V, it is evident that the student study groups are formed based on generalized composition criteria used to classify students in their respective study classes. The grouping results demonstrate both the diversity among the members of study groups and the similarity within the groups.

Based on Fig 13 and the results of previous studies, it is evident that the overall grouping of learning requires improved formulations to achieve a better distribution for the formation of student learning classes. The resulting class division can be observed in Table III.

TABLE V: GENETIC ANALYSIS GROUPING

Class Code	Total Students	Male (L)	Female (F)	SNMPTN	SBMPTN	Independent	SMA	SMK	MA
F1	15	12	3	3	4	8	3	10	2
F2	15	9	6	5	7	3	6	8	1
F3	14	8	6	4	5	5	3	9	2
F4	14	8	6	3	6	5	4	8	2
F5	14	11	3	5	4	5	8	6	0
F6	14	7	7	1	2	11	3	9	2
F7	14	5	9	4	4	6	7	7	0
F8	14	9	5	7	4	3	5	7	2

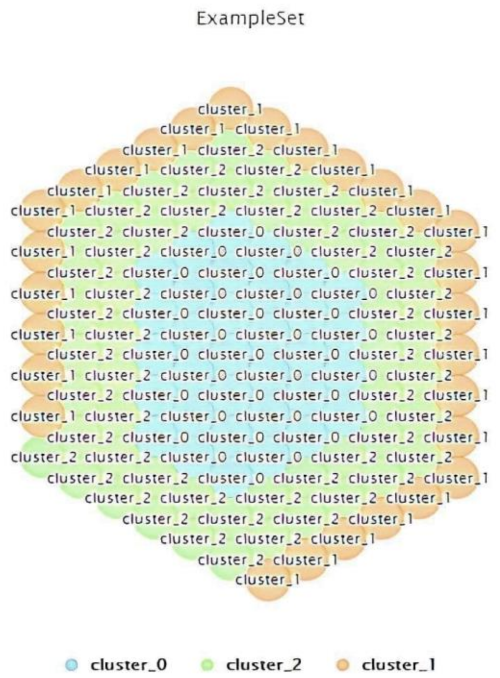

Fig. 13. Student homogeneity clustering.

TABLE VI: GROUPING DISTRIBUTION K-MEANS CLUSTERING

	F1	F2	F3	F4	F5	F6	F7	F8
L	11	9	10	9	7	7	8	8
P	4	6	4	5	7	7	6	6
SNMPTN	4	4	5	4	5	5	5	4
SBMPTN	6	6	4	4	3	3	3	5
INDEPENDENT	5	5	5	6	6	6	6	5
SMK	3	5	4	6	6	4	7	6
SENIOR HIGH SCHOOL	11	7	9	6	6	10	7	7
MA	1	3	1	2	2	0	0	1

The results demonstrate that the genetic algorithm efficiently optimizes the arrangement of student compositions in groupings by effectively distributing the criteria that contribute to the variations among students in each class. In contrast, the K-means algorithm does not directly facilitate the grouping of learning classes; it necessitates clustering based on predefined provisions and additional algorithms to distribute cluster results for the formation of learning class groups. A visual comparison of these approaches can be observed in Figs. 14 and 15.

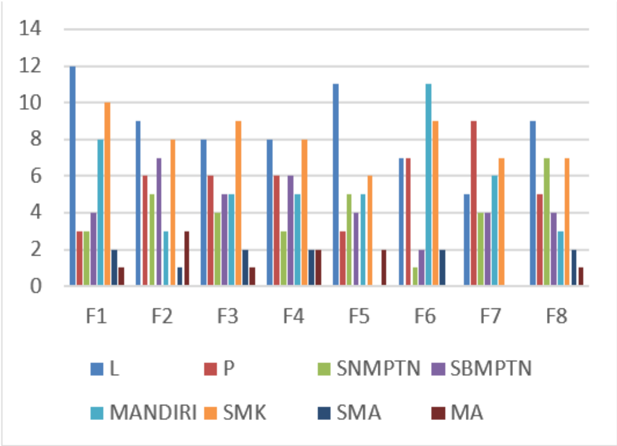

Fig. 14. Graph result grouping genetic's algorithm.

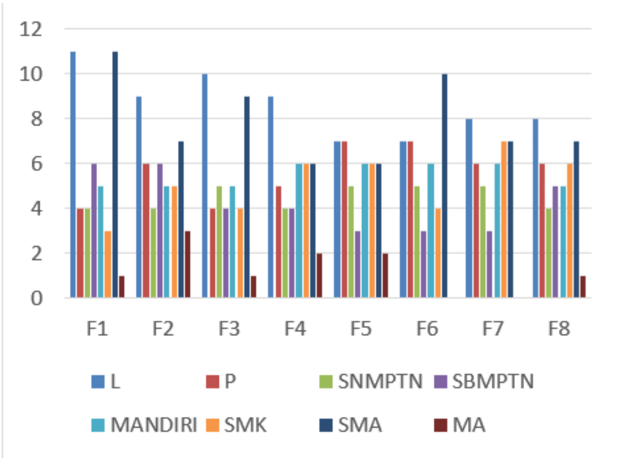

Fig. 15. Graph result grouping distributed K-means clustering.

The formation of heterogeneous classes aims to mitigate learning risks, such as reduced incidents of bullying among students, facilitation for teachers in selecting appropriate methods and strategies for instruction, and the reduction of social inequalities that may arise in the learning environment. Genetic algorithms present an effective alternative for grouping learning classes in the field of engineering education. Engineering education possesses unique characteristics and requires specialized learning content. Genetic algorithms yield optimal outcomes when applied to group students based on multiple criteria. Additionally, this grouping process influences the alignment of learning styles and strategies employed by instructors. It is anticipated that these factors will have a positive impact on the academic achievement and performance of students in technical education [14, 34, 57–60].

IV. Discussion

This research presents intriguing findings on the application of genetic algorithms in grouping learning classes that exhibit intra-heterogeneity and inter-homogeneity. Our findings demonstrate that genetic algorithms provide an effective and adaptive approach to address individual learning needs and optimize the formation of learning groups. By leveraging this approach, students can be assigned to learning groups that align with their specific requirements, encompassing learning styles and skill levels. This promotes an inclusive learning environment where students can learn from one another and provide mutual support.

Genetic algorithms inherently embody the principles of constructivism within the context of learning group formation. In genetic algorithms, each individual in the population represents a distinct learning solution, and through an evolutionary process involving selection, recombination, and mutation, these solutions evolve and improve over time. This process mirrors the principles of natural selection, resulting in progressively enhanced solutions [39].

A study conducted by Sukstrienwong [61] investigated the application of genetic algorithms in grouping heterogeneous students. The findings of this study demonstrated that genetic algorithms were successful in forming heterogeneous learning groups that accounted for students' diverse skill levels. This enabled students to engage in collaborative learning and provide mutual support to one another.

While genetic algorithms offer a powerful approach for optimizing the formation of heterogeneous learning classes, it is important to consider several constraints: (1) Genetic algorithms can sometimes become trapped in suboptimal solution that do not achieve the desired level of heterogeneity [62]; (2) The computational process involved in forming heterogeneous groups can be complex and time-consuming [63]; (3) Accurately representing student characteristics is crucial for the success of genetic algorithms [64]; (4) The complexity of group formation rules and meeting constraints presents challenges in the optimization process [65]; (5) Objective evaluation of the effectiveness of genetic algorithms in forming heterogeneous groups can be subjective due to various factors.

V. Conclusion

This research demonstrates the intriguing and effective use of genetic algorithms to optimize the grouping of learning classes for students, particularly in the context of engineering education. By considering the individual differences among students as grouping criteria, genetic algorithms offer a valuable approach to enhance the learning experience.

In the genetic algorithm process, students are represented as initialized genes with associated variable values. Chromosomes are then implemented to encode class or group codes, and the population represents the number of student classes. Through experimentation, we achieved the formation of eight student study groups, each consisting of approximately 15 students with well-balanced grouping criteria.

The application of genetic algorithms allowed us to generate both intra-heterogeneous and inter-homogeneous study groups. These optimized groups are expected to have a positive impact on the performance and academic achievements of students in engineering education.

Overall, this research highlights the significance of genetic algorithms in facilitating the formation of diverse and well-structured learning groups. By leveraging individual differences and utilizing the power of genetic algorithms, we can create an inclusive and effective learning environment for students in engineering education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mr. Denny Kurniadi oversees all research development, while Mr. Hendra Hidayat and Mr. Muhammad Anwar led the writing of the script. The data was analyzed by Mr. Khairi Budayawan. Abdurrasyid Luthfi Syaifar and Rahmadona Safitri conducted the research. Mr. Zulhendra and Mr. Efrizon were responsible for developing theoretical formalism and script writing. All authors have approved the final version.

References

[1] J. Martín-Gutiérrez, C. E. Mora, B. Añorbe-Díaz, and A. González-Marrero, "Virtual technologies trends in education," E*urasia J. Math. Sci. Technol. Educ.*, vol. 13, no. 2, pp. 469–486, 2017, doi: 10.12973/eurasia.2017.00626a

[2] X. Yin, "Construction of student information management system," *Complexity*, vol. 2021, 4447045, 2021.

[3] Y. A. Wijaya, D. A. Kurniady, E. Setyanto, W. S. Tarihoran, D. Rusmana, and R. Rahim, "Davies Bouldin index algorithm for optimizing clustering case studies mapping school facilities," *TEM J.*, vol. 10, no. 3, pp. 1099–1103, 2021, doi: 10.18421/TEM103-13

[4] N. Fachada, "ColorShapeLinks: A board game AI competition for educators and students," *Comput. Educ. Artif. Intell.*, vol. 2, 100014, 2021, doi: 10.1016/j.caeai.2021.100014

[5] R.-C. Roman, R.-E. Precup, and E. Petriu, "Hybrid data-driven fuzzy active disturbance rejection control for tower crane systems," *Eur. J. Control*, vol. 58, Aug. 2020, doi: 10.1016/j.ejcon.2020.08.001

[6] Q. Liu, S. Ba, J. Huang, L. Wu, and L. Chuanyuan, "A study on grouping strategy of collaborative learning based on clustering algorithm," in *Proc. International Conference on Blended Learning*, 2017. doi: 10.1007/978-3-319-59360-9_25

[7] J. E. Thistlethwaite *et al.*, "The effectiveness of case-based learning in health professional education. A BEME systematic review: BEME Guide No. 23," *Med. Teach.*, vol. 34, no. 6, pp. 421–444, 2012, doi: 10.3109/0142159X.2012.680939

[8] M. Credé, S. G. Roch, and U. M. Kieszczynka, "Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics," *Rev. Educ. Res.*, vol. 80, no. 2, pp. 272–295, 2010, doi: 10.3102/0034654310362998

[9] R. S. Davies, D. L. Dean, and N. Ball, "Flipping the classroom and instructional technology integration in a college-level information systems spreadsheet course," *Educ. Technol. Res. Dev.*, vol. 61, no. 4, pp. 563–580, 2013, doi: 10.1007/s11423-013-9305-6

[10] M. Friend, L. Cook, D. Hurley-Chamberlain, and C. Shamberger, "Co-teaching: An illustration of the complexity of collaboration in special education," *J. Educ. Psychol. Consult.*, vol. 20, no. 1, pp. 9–27, 2010, doi: 10.1080/10474410903535380

[11] L. Florian and K. Black-Hawkins, "Exploring inclusive pedagogy," *Br. Educ. Res. J.*, vol. 37, no. 5, pp. 813–828, 2011, doi: 10.1080/01411926.2010.501096

[12] J. T. Avella, M. Kebritchi, S. G. Nunn, and T. Kanai, "Learning analytics in distance education: A systematic literature review," *Online Learn.*, vol. 20, no. 2, pp. 13–29, 2016.

[13] R. Cerezo, M. Sánchez-Santillán, M. P. Paule-Ruiz, and J. C. Núñez, "Students' LMS interaction patterns and their relationship with achievement: A case study in higher education," *Comput. Educ.*, vol. 96, pp. 42–54, 2016, doi: 10.1016/j.compedu.2016.02.006

[14] H. Hidayat *et al.*, "The empirical analysis of industrial work challenges in the industrial revolution 5.0 towards a Grade Point Average (GPA) for electronic engineering education students," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 17, no. 09, pp. 21–34, 2021.

[15] E. Syahmaidi, H. Hidayat, S. Hartanto, and A. F. Rahmadani, "Needs analysis of designing online computer-assisted training to improve pedagogical competencies in engineering education," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 8958, no. 6, pp. 4619–4624, 2019, doi: 10.35940/ijeat.F8905.088619

[16] B. Sacerdote, "Peer effects in education: How might they work, how big are they and how much do we know thus far?" in *Handbook of the Economics of Education*, E. A. Hanushek, S. Machin, and L. Woessmann, Eds. vol. 3, no. 11, Elsevier B. V., 2011, doi: 10.1016/B978-0-444-53429-3.00004-1

[17] S. Winton, "Character development and critical democratic education in Ontario, Canada," *Leadersh. Policy Sch.*, vol. 9, no. 2, pp. 220–237, 2010, doi: 10.1080/15700760903100758

[18] D. A. Cook and A. R. Artino, "Motivation to learn: An overview of contemporary theories," *Med. Educ.*, vol. 50, no. 10, pp. 997–1014, 2016, doi: 10.1111/medu.13074

[19] P. L. Curşeu and H. Pluut, "Student groups as learning entities: The effect of group diversity and teamwork quality on groups' cognitive complexity," *Stud. High. Educ.*, vol. 38, no. 1, pp. 87–103, 2013, doi: 10.1080/03075079.2011.565122

[20] B. Seijo-Pardo, I. Porto-Díaz, V. Bolón-Canedo, and A. Alonso-Betanzos, "Ensemble feature selection: Homogeneous and heterogeneous approaches," *Knowledge-Based Syst.*, vol. 118, pp. 124–139, 2017, doi: 10.1016/j.knosys.2016.11.017

[21] E. H. Chiriac, "Group work as an incentive for learning â€" studentsâ€TM experiences of group work," *Front. Psychol.*, vol. 5, 2014, doi: 10.3389/fpsyg.2014.00558

[22] R. Valls and L. Kyriakides, "The power of interactive groups: How diversity of adults volunteering in classroom groups can promote inclusion and success for children of vulnerable minority ethnic populations," *Cambridge J. Educ.*, vol. 43, no. 1, pp. 17–33, 2013, doi: 10.1080/0305764X.2012.749213

[23] J. A. Smith, M. McPherson, and L. Smith-Lovin, "Social distance in the United States: Sex, race, religion, age, and education homophily among confidants, 1985 to 2004," *Am. Sociol. Rev.*, vol. 79, no. 3, pp. 432–456, 2014, doi: 10.1177/0003122414531776

[24] R. M. Oliver, J. H. Wehby, and D. J. Reschly, "Teacher classroom management practices: effects on disruptive or aggressive student behavior," *Campbell Syst. Rev.*, vol. 7, no. 1, pp. 1–55, 2011, doi: 10.4073/csr.2011.4

[25] S. McCoy and D. Byrne, " 'The sooner the better I could get out of there': Barriers to higher education access in Ireland," *Irish Educ. Stud.*, vol. 30, no. 2, pp. 141–157, 2011, doi: 10.1080/03323315.2011.569135

[26] H. M. Matusovich, R. A. Streveler, and R. L. Miller, "Why do students choose engineering? A qualitative, longitudinal investigation of students' motivational values," *J. Eng. Educ.*, vol. 99, no. 4, pp. 289–303, 2010, doi: 10.1002/j.2168-9830.2010.tb01064.x

[27] J. Dunlosky, K. A. Rawson, E. J. Marsh, M. J. Nathan, and D. T. Willingham, "Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology," *Psychol. Sci. Public Interes. Suppl.*, vol. 14, no. 1, pp. 4–58, 2013, doi: 10.1177/1529100612453266

[28] S. Pokhrel and R. Chhetri, "A literature review on impact of COVID-19 pandemic on teaching and learning," *High. Educ. Futur.*, vol. 8, no. 1, pp. 133–141, 2021, doi: 10.1177/2347631120983481

[29] A. T. Venables and G. Tan, "A 'Hands on' strategy for teaching genetic algorithms to undergraduates," *J. Inf. Technol. Educ. Res.*, vol. 6, pp. 249–261, 2007, doi: 10.28945/214

[30] M. F. Peschl, "Constructivism, cognition, and science—An investigation of its links and possible shortcomings what is science? What are its goals? What are its typical means of investigation and construction of knowledge? Why is science playing such an importan," *Science*, vol. 80, pp. 125–161, 2001.

[31] N. Jumaat, Z. Tasir, N. Abd halim, and Z. Mohamad Ashari, "Project-based learning from constructivism point of view," *Adv. Sci. Lett.*, vol. 23, pp. 7904–7906, Oct. 2017, doi: 10.1166/asl.2017.9605

[32] Z. Amrina, R. Desfitri, F. Zuzano, Y. Wahyuni, H. Hidayat, and J. Alfino, "Developing instruments to measure students' logical, critical, and creative thinking competences for bung Hatta university students," *International Journal of Engineering & Technology*, vol. 7, pp. 128–131, 2018.

[33] H. Hidayat, B. Tamin, S. Herawati, A. Hidayati, and A. Muji, "Implementation of technopreneurship scientific learning for produce electronic product prototypes in engineering education," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, pp. 2842–2846, Sep. 2019, doi: 10.35940/ijitee.K2406.0981119

[34] H. Hidayat, B. Tamin, S. Herawati, Z. Ardi, and A. Muji, "The contribution of internal locus of control and self-concept to career maturity in engineering education," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, p. 2282, Dec. 2020, doi: 10.18517/ijaseit.10.6.11698

[35] S. M. Elsayed, R. A. Sarker, and D. L. Essam, "A new genetic algorithm for solving optimization problems," *Eng. Appl. Artif. Intell.*, vol. 27, pp. 57–69, 2014, doi: 10.1016/j.engappai.2013.09.013

[36] J. Moreno, D. A. Ovalle, and R. M. Vicari, "A genetic algorithm approach for group formation in collaborative learning considering multiple student characteristics," *Comput. Educ.*, vol. 58, no. 1, pp. 560–569, 2012, doi: 10.1016/j.compedu.2011.09.011

[37] A. Sukstrienwong, "A cyclic-genetic-algorithm approach to composing heterogeneous groups of students," *Tem Journal*, vol. 5, no. 6, Jan. 2016, doi: 10.18421/TEM54-09

[38] K. Deb, *Multi-objective Optimization Using Evolutionary Algorithms*, Wiley, New York, 2001.

[39] A. Krouska, C. Troussas, and M. Virvou, "Applying genetic algorithms for student grouping in collaborative learning: A synthetic literature review," *Intell. Decis. Technol.*, vol. 13, no. 4, pp. 395–406, 2020, doi: 10.3233/idt-190184

[40] R. Marti and G. Reinelt, "The linear ordering problem: Exact and heuristic methods in combinatorial optimization," *Springer Berlin*, vol. 175, 2011. doi: 10.1007/978-3-642-16729-4

[41] V. Yannibelli and A. Amandi, "A deterministic crowding evolutionary algorithm to form learning teams in a collaborative learning context," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 8584–8592, 2012, doi: 10.1016/j.eswa.2012.01.195

[42] S. Mirjalili, J. Song Dong, A. S. Sadiq, and H. Faris, "Genetic algorithm: Theory, literature review, and application in image reconstruction," *Springer International Publishing*, vol. 811, 2020, doi: 10.1007/978-3-030-12127-3_5

[43] P. Snaselova and F. Zboril, "Genetic algorithm using theory of chaos," *Procedia Comput. Sci.*, vol. 51, no. 1, pp. 316–325, 2015, doi: 10.1016/j.procs.2015.05.248

[44] Y. Li, L. Zhao, and S. Zhou, "Review of genetic algorithm," *Adv. Mater. Res.*, vol. 179–180, pp. 365–367, 2011, doi: 10.4028/www.scientific.net/AMR.179-180.365

[45] R. Leardi, "Genetic algorithms," *Compr. Chemom.*, vol. 1, pp. 631–653, 2009, doi: 10.1016/B978-044452701-1.00039-9

[46] H. Sun, W. Zhang, and N. Xu, "Density functional calculation of structural and electronic properties of Tin-xAlx (n =2–8, 13, x=0–n) clusters," *J. Phys. Chem. Solids*, vol. 118, pp. 126–136, 2018, doi: 10.1016/j.jpcs.2018.01.029

[47] J. S. Chou, M. Y. Cheng, Y. W. Wu, and A. D. Pham, "Optimizing parameters of support vector machine using fast messy genetic algorithm for dispute classification," *Expert Syst. Appl.*, vol. 41, no. 8, pp. 3955–3964, 2014, doi: 10.1016/j.eswa.2013.12.035

[48] P. De Lit, E. Falkenauer, and A. Delchambre, "Grouping genetic algorithms: An efficient method to solve the cell formation problem," *Science Direct*, vol. 51, pp. 257–271, 2000.

[49] O. Somantri, I. Afriliana, and E. Budihartono, "An optimized model for classification of appropriate technology products using neural networks and genetic algorithms an optimized model for classification of appropriate technology products using neural networks and genetic algorithms," in *Proc. the 2nd International Conference on Computer Science and Engineering Technology*, 2020, doi: 10.1088/1742-6596/1430/1/012035

[50] A. G. Delavar, V. Aghazarian, S. Litkouhi, and M. K. naeini, "A scheduling algorithm for increasing the quality of the distributed systems by using genetic algorithm," *Int. J. Inf. Educ. Technol.*, vol. 1, no. 1, pp. 58–62, 2011, doi: 10.7763/ijiet.2011.v1.10

[51] J. L. Torres and N. B. Linsangan, "Application of genetic algorithm for optimization of data in surface myoelectric prosthesis for the Transradial amputee," *Int. J. Inf. Educ. Technol.*, vol. 5, no. 2, pp. 113–118, 2015, doi: 10.7763/ijiet.2015.v5.486

[52] L. Ollesch, J. Kohlmann, M. Steiner, O. Tasdelen, and D. Bodemer. "uniMatchUp!: An application for promoting academic help-seeking and group development," University of Duisburg-Essen, 2022.

[53] A. Sukstrienwong, "Group formation based on students' learning styles by circular genetic algorithm," *TEM Journal*, vol. 10, no. 3, pp. 1016–1021, 2021, doi: 10.18421/TEM103
[54] A. Sukstrienwong, "ANOVA as fitness function for genetic algorithm in group composition," *TEM Journal*, vol. 12, no. 1, pp. 396–405, 2023, doi: 10.18421/TEM121
[55] H. I. Toshev, S. L. Koynov, and C. D. Korsemov, "A modular system for solving optimization problems by testing them with genetic algorithms," in *Proc. ICEST 2020*, pp. 647–650.
[56] R. Chi, H. Li, D. Shen, Z. Hou, and B. Huang, "Enhanced P-type control: indirect adaptive learning from set-point updates," *IEEE Trans. Automat. Contr.*, 22685750, Jan. 2022, doi: 10.1109/TAC.2022.3154347
[57] M. Anwar, H. Hidayat, I. P. Yulistiowarno, K. Budayawan, O. A. Osumah, and Z. Ardi, "Blended learning based project in electronics engineering education courses: A learning innovation after the Covid-19 pandemic," *iJIM*, vol. 16, no. 14, pp. 107–122, 2022.
[58] E. Tasrif, H. K. Saputra, D. Kurniadi, H. Hidayat, and A. Mubai, "Designing website-based scholarship management application for teaching of Analytical Hierarchy Process (AHP) in Decision Support Systems (DSS) subjects," *iJIM*, vol. 15, no. 09, pp. 179–191, 2021.
[59] Ganefri, H. Hidayat, A. Yulastri, and S. Yondri, "Design of production-based entrepreneurship technology training model to improve the skills of engineering students," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, pp. 2042–2047, Sep. 2019, doi: 10.35940/ijitee.K1930.0981119
[60] Ganefri, R. Fadillah, and H. Hidayat, "Designing interface based on Digipreneur to increase entrepreneurial interest in engineering students," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, pp. 78–84, Jan. 2022, doi: 10.18517/ijaseit.12.1.13915
[61] A. Sukstrienwong, "A genetic algorithm approach for forming heterogeneous groups of students," *Int. J. Appl. Eng. Res.*, vol. 9, pp. 297–311, Jan. 2014.
[62] K. Matou, M. Lep, J. Zeman, and M. Sejnoha, "Applying genetic algorithms to selected topics commonly encountered in engineering practice," *Science Direct*, vol. 190, 2000.
[63] A. Sukstrienwong, "A method of genetic algorithm for forming student groups based on heterogeneous grouping," *Far East J. Math. Sci.*, vol. 95, pp. 95–110, Dec. 2014.
[64] T. Lakshmi, M. Aruldoss, and V. Venkatesan, "An Analysis of students performance using genetic algorithm," *J. Comput. Sci. Appl.*, vol. 1, pp. 75–79, Jan. 2013, doi: 10.12691/jcsa-1-4-3
[65] A. Krouska, C. Troussas, and C. Sgouropoulou, "A novel group recommender system for domain-independent decision support customizing a grouping genetic algorithm," *User Model. User-adapt. Interact.*, 2023, doi: 10.1007/s11257-023-09360-3