Group Formation Using Multi Objectives Ant Colony System for Collaborative Learning

Fitra Zul Fahmi[1], Dade Nurjanah[2]
School of Computing
Telkom University
Bandung, Indonesia
[1]fitradzulfahmi@gmail.com.
[2]dadenurjanah@telkomuniversity.ac.id

***Abstract*—Collaborative learning is widely applied in education. One of the key aspects of collaborative learning is group formation. A challenge in group formation is to determine appropriate attributes and attribute types to gain good group results. This paper studies the use of an improved ant colony system (ACS), called Multi Objective Ant Colony System (MOACS), for group formation. Unlike ACS that transforms all attribute values into a single value, thus making any attributes are not optimally worth, MOACS tries to gain optimal values of all attributes simultaneously. MOACS is designed for various combinations of attributes and can be used for homogeneous, heterogeneous or mixed attributes. In this paper, sensing/intuitive learning styles (LSSI) and interests in subjects (I) are used in homogeneous group formation, while active/reflective learning style (LSAR) and previous knowledge (KL) are used for heterogeneous or mixed group formation. Experiments were conducted for measuring the average goodness of attributes (avgGA) and standard deviation of goodness of attributes (stdGA). The objectives of MOACS for homogeneous attributes were minimum avgGA and stdGA, while those for heterogeneous attributes were maximum avgGA and minimum stdGA. As a conclusion, MOACS was appropriate for group formation with homogeneous or mixed.**

Keywords*— Collaborative learning, ACS, MOACS, group formation, homogenous group, heterogeneous group, mixed group

I. INTRODUCTION

The combination of learning method and social science has led to the development of collaborative learning in which students learn through group learning activities. The objective of group learning activities is that learners can individually gain knowledge by doing group work and interacting with peer learners. Tasks in group learning activities require learners to work together to solve problems, discover information, and complete projects [1]. Collaborative learning is a learning approach to improve social ability, practice skill, and experience, and enhance communication between [2][3][4]. In practicing collaborative learning in a class, teachers are required to perform a number of groups of learners.

Group formation is a key factor for supporting the success of collaborative learning activity [4][5]. The main objective of group formation is to build fair and effective groups [6][7], which can be achieved by finding appropriate attributes and methods. Group formation is important to support fairness and effectiveness of collaborative learning [6 [5]. The fairness is related to students' feeling of convenience and happiness when working in a group [6]. The effectiveness refers to the opportunities of students participating in learning activities and gaining benefits from the group work, such as communication skill ability, knowledge, etc. In group formation, several aspects such as psychology, sociology, philosophy and education must be considered.

With the growth of information technology, collaborative learning is influenced by recent technologies of information; it is called computer-supported collaborative learning (CSCL). Group formation in CSCL is not a manual process anymore. The complexity of group formation has been increased because the group formation attributes and constraints are more and more varied. Group formation is an NP-Hard problem [8]. Previous research has studied various methods for group formation, such as rule/inference [9], Multi-agent [10] [11], Greedy algorithm [12], Genetic Algorithm [13], Hill Climbing [14], Fuzzy C-Means [15], Ant Colony Optimization [16] , and Semantic Web [8].

One of the challenges and issues in group formation system is how to combine learners' attributes which are considered good for performing homogeneous or heterogeneous groups. In this study, we start our work by reviewing and analyzing critical design issues of group formation and organize them according to some classification schemes. So that, it can help teachers to develop group formation system based on their cases. The various criteria or attributes have been applied in group formation, such as knowledge or expertise in a specific domain [9][15], learning goal [10], learners' performance in previous teamwork [10][16], personality traits [16], learning style [8][17][18], thinking style [13], Belbin role and minority [8], and preferred time slots and project [12].

This paper discusses our research on group formation. We applied the Multi Objective Ant Colony System (MOACS). This research accommodates different combinations of attributes for various objectives of grouping that lead to homogeneous, heterogeneous, or mixed groups. The remainder of this paper is organized as follows. Section 2 discusses our study on previous research on group formation. Section 3 explains MOACS for group formation and Section 4 is about the experiments and results. Finally, Section 5 presents conclusions and the future work.

II. GROUP FORMATION

There are three types of groups: heterogeneous, homogeneous and mixed groups [19]. Homogeneous groups have members with similar levels or homogeneous values of learners' attributes. Homogeneous groups, however, offer more advantages than heterogeneous groups when applied to skill exercises and guided discovery learning activities. On the other hand, heterogeneous groups consist of members with different levels, values or types of grouping criteria or attributes. Heterogeneous groups are appropriate for in-class problem solving (create journals, project, analysis of some cases) and long-term problem solving projects.

A former study has concluded chances to gain success, as it offers an opportunity for learners to be more innovative and creative [20]. Furthermore, some research has proved that heterogeneous groups support learners more to achieve learning goals than homogeneous groups [17][18][20]. The heterogeneity of the members means the groups have many resources. Every member gains rich and various points of view and opinions in groups rising from different personalities, experience, learning styles, etc. Combining both types has resulted in mixed groups, which are groups that consist of members with a combination of homogeneous and heterogeneous attributes. Homogeneous and heterogeneous attributes are not constraints to be strictly separated. Groups may have both heterogeneous and homogeneous attributes.

Another important attribute that must be considered is group size. Group size becomes an important parameter as it influences communication and relationships between group members. There is a useful point about group size, that is the larger the group size, the more groups can provide resource contribution, knowledge sharing, diversified skills and opportunities to meet other individuals with related interests. On the other hand, when group size increases, new problems tend to appear, such as difficulties in group organizational management, social loafing, free riding, trouble with monitoring behaviour of members, production blocking, evaluation apprehension, reduction in group ability to coordinate and collaborate, and pressure on individuals to conform [21]. Previous studies have revealed that smaller groups have promoted individual participation, greater satisfaction, more time for discussion, and an enhanced perception that contributions of members are vital to the success of the process [21]. Group size should not be based on convenience or instructor preference, but rather the type of tasks and the number of members required in accomplishing the task [21]. Slavin [4] proposed that the size of group formation is four persons with mixed ability members, for example one has high achievement, two have average achievement, and the other has low achievement. Another research [13] formed groups with three members each. Furthermore, another study suggested an optimal size of a group based on learning objectives [22], including skill exercises (teams of two), guided discovery Learning (teams of three), in-class problem solving (teams of four), and long-term problem solving project (teams of five).

There are a number of grouping attributes that have been used in previous studies. Among such group attributes, learning styles, thinking styles, personality types, personality traits and team role are the most used attributes.

1) Learning Style

A previous study by Liu et al. [23] used active/reflective dimensions of the Felder and Silverman learning style model to form groups [24]. They applied similar learning styles for doing the first task and diverse learning style for doing the second task. The study showed that applying diverse learning styles mean learners have more meaningful interaction and fewer disagreements in the group collaboration work. Another study [17] used other dimensions of learning styles, active-reflective, and sensing-intuitive. It affected the quality of learners' group work. Diverse learning styles make learners become aware of their own strengths and weaknesses, as well as their team mates' strengths and weaknesses. Knowing their team mates' characteristics made learners honor differences among them, talents and competence [25].

2) Thinking Style

Thinking style refers to a way for learners to find a solution to their problem. A previous study [13] found that there is a correlation between learners' attitudes and cooperation with group outcomes. Grouping considering thinking styles resulted in better groups in that they show less variance in group performance than randomly assigned groups do.

3) Personality Traits

A previous study found that learners grouped based on the performance level and personality attributes (traits) performed better than randomly-assigned or self-selected groups [20].

4) Team Role

Groups in some cases need to assign different roles to their member. It has been proved that the right role assignment resulted in good performance in a group [8].

III. Our Research: Group Formation using MOACS Algorithm

The idea of using Ant Colony Optimization (ACO) for group formation system has been proposed by [16] and [20]. In previous study, ACO transform all attribute's score become single score, thus making any attributes are not optimally worth. In this study, we apply MOACS that enables to group learners and combine homogeneous or heterogeneous attributes of learners. MOACS tries to gain optimal score of all attributes simultaneously. MOACS consists of five phases, including initialization, exploitation, and exploration, finding the best fitness score, and local / global updating rule.

A. Group Attributes and Constraints

Grouping attributes is one key aspect to form a group which are gathered from learners. Instructors or teachers must choose the group attributes before starting group formation. However, MOACS can use only attributes that have a score range between 0 and 1 and the attribute has qualitative evaluation by previous literature**.** Learners' attributes used in group formation in this research consist of:

1) Previous knowledge level

Previous knowledge level is learners' expertise relevant to course or materials. This attribute usually is obtained from the grade in prerequisite course or pre-test before study. The different levels of knowledge between learners in one group can support interaction between learners with high knowledge and low knowledge [20].

2) Experience

Experience is related to learners' experience about specific cases or projects that learners have to solve it. The similar level of experience in one group can give each learner an opportunity to grow [8]. When learners have an opportunity to grow, learners will do the best together to reach the project goal.

3) Learning style

Learning style has four dimensions: active/reflective, sensing/intuitive, global/sequential, and verbal/visual. Our study applies two attributes, which are active/reflective and sensing/intuitive. Placing different learners with active and reflective learning style can raise meaningful interaction among them [20]. In contrast, placing similar learners with either sensing or intuitive dimension in one group will benefit learners [15][24][25].

4) Interest in a subject [26][27]

Every learner has interests in some subjects. The subjects can be hobbies, knowledge, music, movie, sport, or others. Different interests of learners can enrich group members' knowledge and experience when sharing knowledge or story. Similar interests of learners can motivate the group to engage in a higher level of interaction, that learners with high interest can motivate other learners with low interests.

5) Thinking style in functionality dimension

Thinking style in functionality dimension consists of three attributes: legislative, executive, and judicial. Learners with similar thinking style in functionality dimension can collaborate that will improve learners' attitudes, the collaborative work, and group outcomes [13].

The type and value range of each attribute are shown in Tabel 1.

Table 1 Group Formation Attributes

Attributes	Type, Range Value	Normalized	Labels
Prior knowledge level or score of previous course or task	Heterogeneous, Between 0 and 100	[0..1]	High/ Moderate/ Low
Learning style in Active/Reflective dimension	Heterogeneous, Between -11 and 11	[0..1]	Active/ Neutral/ Reflective
Learning style in sensing/Intuitive dimension	Homogeneous, Between -11 and 11	[0..1]	Sensing/ Neutral/ Intuitive
Thinking style in functionality dimension	Homogeneous, Between 0 and 100	[0..1]	Legislative/ Executive/ Judical
Learner's interest in a subject	Heterogeneous, Between 0 and 10	[0..1]	Interested/ Medium/ Uninterested

B. Algorithm: Multi-Objectives Ant Colony System

Figure 1 shows how group formation is done with MOACS.

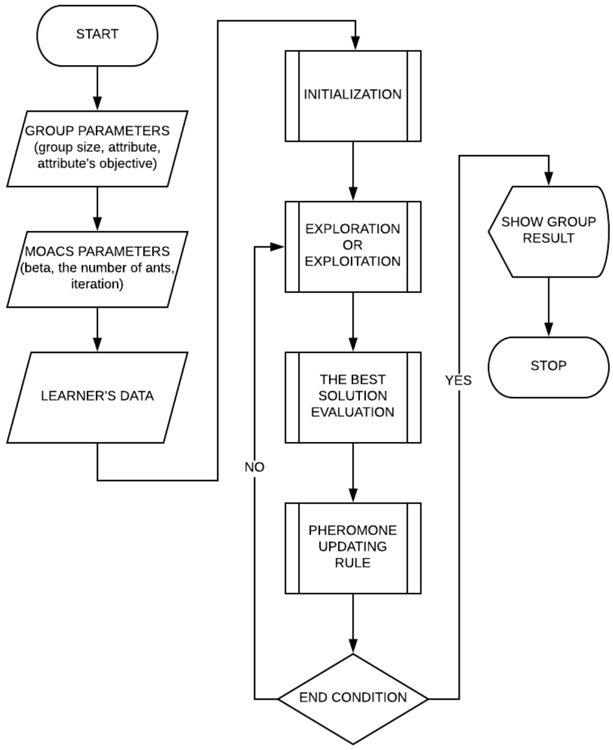

Figure 1 Group Formation using MOACS

1) Initialization Phase

In multi-objective ant colony system (MOACS) problem, every solution by ant is measured according to more than one objective function, each of which must be minimized or maximized [28][29]. In group formation problem using MOACS, the objective function is the objective of attribute that must be heterogeneous (maximized) or homogeneous (minimized). The group formation problem is modelled as a complete graph that represents the closeness among learners. The learner's attributes for learner n-th that have r attributes are modelled by $L_n = [C(0), C(1), \dots, C(r)]$. The closeness among learners is measured according to each learner's attributes using Euclidean distance and represent by closeness matrices $[M_{C(0)}, M_{C(1)}, \dots, M_{C(r)}]$. Here is the formula for calculating distance between two learners for the *r-th* attribute.

$$M_{C(r)}(L_n, L_{n+1}) = \sqrt{\sum (C(r)_{Ln} - C(r)_{Ln+1})^2} \qquad (1)$$

The proposed MOACS uses an ant to simultaneously optimize all objectives: the homogeneous attribute is minimized and heterogeneous attribute is maximized, because all attributes and their objectives are all important. All objectives share the same pheromone trails. In every iteration, an ant k ($\forall k \in \{1,2,\dots,Nants\}$, Nants is the number of ant in a colony that construct one feasible group solution and after ants have solution, the best solution will be chosen. The key of MOACS for group formation is how to determine the state transition rule (exploration and exploitation), group quality function, and the best solution evaluation and global updating rule.

2) Exploration and Exploitation

Every ant does exploration and exploitation to choose group member. An ant selects the first member of the group using an exploration formula and the second member until the last member in a group using an exploitation formula. If the targeted number of members is four, the ant will do exploration to the first member and then do exploitation to member 2 until 4. After that, for the next group, firstly, the ant does exploration and it continues with exploitation until all learners have been visited. When ant in learner i and selects the next member (let say learner j), the ant will use the exploitation formula given by:

$$j = \begin{cases} argmax_{j \in N_i^k} \left\{ \tau_{ij} \cdot \left([\eta_{ij}^{c(0)}]^{\lambda} . [\eta_{ij}^{c(1)}]^{\left|\frac{1}{r-1} - \lambda\right|} \ldots . [\eta_{ij}^{c(r)}]^{\left|\frac{r-1}{r-1} - \lambda\right|} \right)^{\beta} \right\}, \\ \quad when\ group\ membership \\ randomly\ selected\ from\ N_i^k, when\ choose\ first\ member\ (exploration) \end{cases} \quad (2)$$

$\lambda = \frac{k}{Nants}$ that represent the weight of each attribute and the value depends on the number of attributes r; β represents the relative importance of each attribute with respect to the pheromone trail, given by τ. N_i^k is defined as learner i that has not been chosen by ant k. $\eta_{ij}^{c(r)}$ is the visibility for the objective or maximum distance between learner i and j in attribute r-th. In general, it is formulated in.

$$\eta_{ij}^{c(r)} \begin{cases} \frac{1}{1 - M_{C(r)}(i,j)}, if C(r) \rightarrow homogeneous \\ \frac{1}{M_{C(r)}(i,j)}, if C(r) \rightarrow heterogeneous \end{cases} \quad (3)$$

Homogeneity or heterogeneity is the objective of each attribute. The exploration and exploitation in MOACS correlates to the number of attributes and each attribute's objective.

When an ant does exploration, it will select the learner j randomly from N_i^k learners (N_i^k is learners who have not been chosen by ant k), according to the probability distribution given by the following calculation.

$$p_{ij}^k = \begin{cases} \frac{[\tau_{ij}]\left[[\eta_{ij}^{c(0)}]^{\lambda} . [\eta_{ij}^{c(1)}]^{\left|\frac{1}{r-1} - \lambda\right|} \ldots . [\eta_{ij}^{c(r)}]^{\left|\frac{r-1}{r-1} - \lambda\right|}\right]^{\beta}}{\sum_{j \in N_i^k} [\tau_{ij}]\left[[\eta_{ij}^{c(0)}]^{\lambda} . [\eta_{ij}^{c(1)}]^{\left|\frac{1}{r-1} - \lambda\right|} \ldots . [\eta_{ij}^{c(r)}]^{\left|\frac{r-1}{r-1} - \lambda\right|}\right]^{\beta}}, if\ j \in N_i^k \\ 0, otherwise \end{cases} \quad (4)$$

After an ant has explored and exploited learner's graph and all groups have the same number of members, an ant then checks N_i^k. If there are still learners in N_i^k, it means that there are orphan learners or learners who have not assigned to groups. So that, an ant will ignore the rule that limits the number of members in each group and allocate the learners in N_i^k to appropriate groups. This allocation will happen until there is no member left in N_i^k. The final activity in exploration and exploitation is local updating rule, which is updating of pheromone value in the route that has been explored and exploited by ant k.

$$\tau_{ij} = (1 - \rho).\tau_{ij} + \rho.\tau_0 \quad (5)$$

Furthermore, the initial value of pheromones (τ_0) is also calculated using the following formula.

$$\tau_0 = \frac{1}{n.\overline{G_{C(0)}^{\psi^h}}.\overline{G_{C(1)}^{\psi^h}}.\ldots\ldots.\overline{G_{C(r)}^{\psi^h}}} \quad (6)$$

Where n is the number of learners in a graph, $\overline{G_{C(r)}^{\psi^h}}$, which represents the average goodness of the r-th attribute in the initial solution ψ^h, which is generated randomly.

3) Solution Score

The result of an ant tour is a sequence of groups and their members. The quality of every attribute in each group will be measured by calculating the goodness of attribute score [16]. The goodness of attributes of solution given by ant k (ψ^k) for attribute r-th ($C(r)$) in group i-th could be computed by calculating the average distance (AD) of members in group i-th for the r-th attribute.

$$AD_{C(r)}^{\psi^k}(i) = \frac{maxCscoreof(L_1, L_2, \ldots, L_n) + minCscoreof(L_1, L_2, \ldots, L_n)}{2} \quad (7)$$

Then, the goodness of attributes will calculate by:

$$G_{C(r)}^{\psi^k}(i) = \frac{maxCscoreof(L_1, L_2, \ldots, L_n) - minCscoreof(L_1, L_2, \ldots, L_n)}{const + \sum_j |AD_l - scoreof(L_{j(i)})|} \quad (8)$$

Where $L_{j(i)}$ is the learner-score of the j-th learner in group i-th in solution ψ^k without learner that his score become $maxCscore$ and $minCscore$. Variable const is a constant number that can be set to 1, 0.01, or other. For example, when const is 1, the minimum value of $G_{C(r)}^{\psi^k}(i)$ is 0 and the maximum value is 1, when const is 0.01, the minimum value of $G_{C(r)}^{\psi^k}(i)$ is 0 and the maximum value is 100. The $G_{C(r)}^{\psi^k}(i)$ indicates that the r-th attribute is in good heterogeneity when the score closes to the maximum value or in good homogeneity when the score closes to the minimum value. Until this phase, every group has goodness of attributes as much as the number of attributes (r).

$$F_i^{\psi^k} = \left(G_{C(0)}^{\psi^k}(i), G_{C(1)}^{\psi^k}(i), \ldots \ldots, G_{C(r)}^{\psi^k}(i)\right) \quad (9)$$

After that, the grouping result by an ant is measured by calculating the average goodness of attributes from each group and this result is called Pareto set PK.

$$PK = \left(\overline{G_{C(0)}^{\psi^k}}, \overline{G_{C(1)}^{\psi^k}}, \ldots \ldots, \overline{G_{C(r)}^{\psi^k}}\right) \quad (10)$$

$\overline{G_{C(r)}^{\psi^k}}$ represent the average goodness of attribute *r-th* in solution ψ^k.

4) The Best Solution Evaluation and Global Updating Rule

In each iteration, the solution of each ant is recorded to a Pareto set PK and it is called local non-dominated set. Pareto-optimal set GP is called global non-dominated set, which is the best solution found by ants from the beginning of iteration. The solution in PK will be compared with the solution in Pareto-optimal set GP in order to check the better solution. When the solution in PK is non-dominated by GP, it means that PK is a new Pareto-optimal set, the value of GP and ψ^{GP} is updated by GK and ψ^k. Therefore, for each solution in ψ^{GP} found after one iteration by all ants in one colony, the pheromone information is globally updated according to the following formula.

$$\tau_{ij} = (1 - \rho).\tau_{ij} + \frac{\rho}{\overline{G_{C(0)}^{\psi^{GP}}}.\overline{G_{C(1)}^{\psi^{GP}}}.\ldots\ldots.\overline{G_{C(r)}^{\psi^{GP}}}} \forall (i,j) \in \psi^{GP} \quad (11)$$

$\overline{G^{\psi^{P}}_{C(r)}}$ represents the average goodness of attribute r-th in solution ψ^{GP}.

These four steps are done in each iteration (one colony of ant doing tour) until the end of iteration by all colonies or met the targeted condition.

IV. Experiment and Results

This section discusses the implementation of MOACS for group formation with homogeneous attributes, heterogeneous attributes, or mixed (homogeneous and heterogeneous) attributes. There are three scenarios which apply different types of attributes: homogeneous, heterogeneous, and mixed. Every scenario evaluates orphan learners, the average goodness of attributes (avgGA), and standard deviation (stdGA). MOACS aims to avoid orphan learners, which means that all learners can be grouped. The targeted condition for homogeneous attributes is minimum average goodness of attribute (avgGA) score, while for heterogeneous attributes the targeted condition is the maximum average goodness of attribute (avgGA) score. Standard deviation (stdGA) is used to show the distribution of goodness of attribute score in every group. The more minimum standard deviation, the better the groups resulted. The minimum standard deviation shows that the group result has a balancing goodness of attribute among groups.

The testing scenario was divided into three scenarios according to the types of attributes in group. The three scenarios were group formation using homogeneous for all attributes, group formation using heterogeneous for all attributes, and group formation using homogeneous in some attributes and heterogeneous in some attributes. In every scenario, MOACS was compared with two methods, which were a random method and ant colony by using homogeneous, heterogeneous, and mixed attributes.

A. *Scenario 1 – Homogeneous Attributes*

The objective of the first experiment is to measure the performance of MOACS for homogeneous group formation. MOACS was applied for group formation in Computer Organization and Architecture course with 42 students. It used homogeneous attributes for all attributes. The tasks in Computer Organization and Architecture are multiple choice and essay questions that must be solved by learners individually and then they discuss each solution to find correct answers. The attributes used are learners' interests (I) and learning styles in sensing/intuitive dimension (LSSI). The size of groups was seven as requested by the instructor. The result of grouping was shown in the following chart.

The lowest score in Figure 2 shows a good homogeneous score related to the attributes. MOACS is able to minimize learning style in Sensing/Intuitive dimension (LSSI) attribute. The score variation among learners tends to give a minimum goodness of attribute for homogeneous attribute. On the other hand, for interest in a subject (I) attribute, MOACS result is between the random method and Ant Colony System (ACS). The score variation among learners tends to give a maximum score for homogeneous attributes.

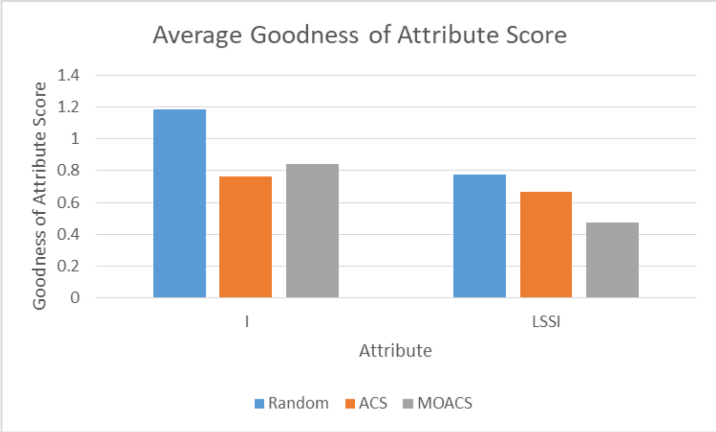

Figure 2 Average Goodness of Attribute Score in Scenario 1

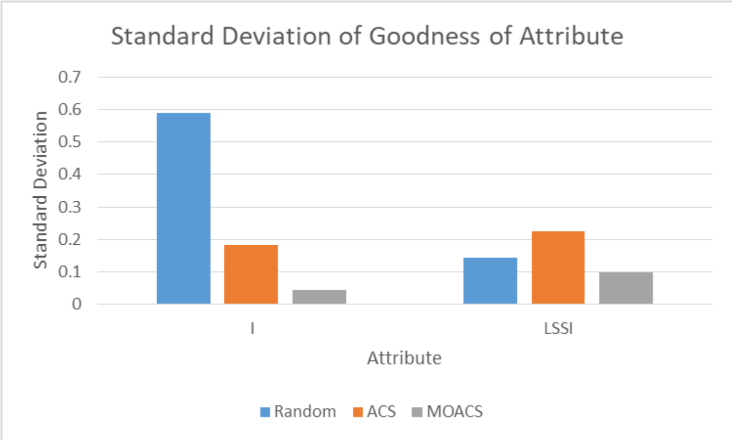

Figure 3 Standard Deviation of Goodness of Attribute in Scenario 1

The lower standard deviation score in Figure 3 shows good group results. MOACS is able to minimize the distribution of goodness of attribute scores in group formation which is better than other methods. The results show the group results have balancing goodness of attributes among groups. The expected result of group formation using homogeneous attributes is minimum avgGA and stdGA. Based on the average goodness of attributes in Figure 2 and standard deviation in Figure 3, MOACS is able to be used for group formation using homogeneous attributes.

B. *Scenario 2 – Heterogeneous Attribute*

The objective of the second experiment is to measure the performance of MOACS for heterogeneous group formation. MOACS was applied in a Design and Analysis Algorithm class with 40 students for grouping learners using heterogeneous attributes. The group task is to create a scientific essay. The attributes used are previous knowledge level (KL) and learning styles in active/reflective dimension (LSAR). The size of group is two. The result of grouping is presented in the figure 4.

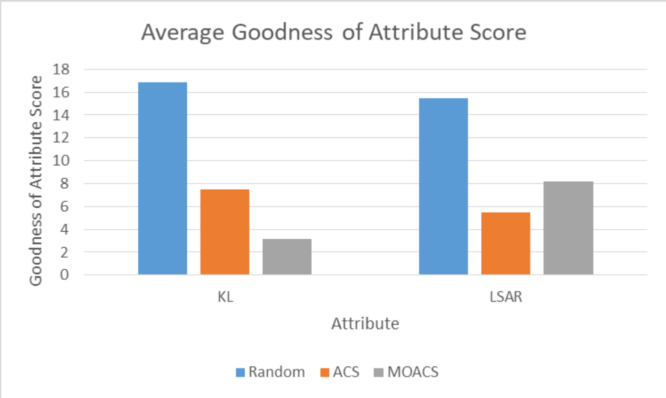

Figure 4 Average Goodness of Attribute Score in Scenario 2

The highest score for heterogeneous attribute in Figure 4 is a good result. MOACS results in low score in knowledge level (KL) and Learning Style in Active/Reflective dimension (LSAR). The knowledge level score has range between 4, 3.5, 3, 2.5, 2 until 1 before normalized to 0-1. The score variation is low, thus making it difficult to gain a maximum goodness of attribute score. Furthermore, LSAR score has range between -11 to 11. Then it is normalized to 0-1. The score variation in each learner tends to give a maximum goodness of attribute for heterogeneous attributes.

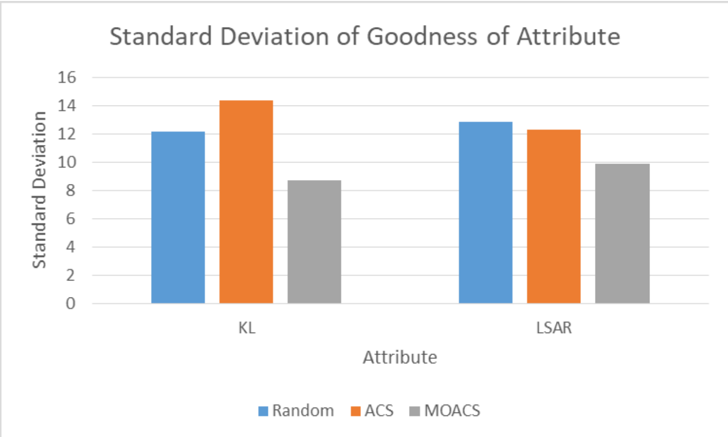

Figure 5 Standard Deviation of Goodness of Attribute in Scenario 2

The result in Figure 5 shows that MOACS is able to minimize the distribution of attribute in every group. MOACS is able to minimize the distribution of goodness of attributes scores in group formation. The result shows balanced goodness of attribute among groups. The expected result of group formation using heterogeneous attribute is the maximum avgGA and minimum stdGA. Based on the average goodness of attribute in Figure 4 and standard deviation in Figure 5, MOACS is not appropriate for group formation using heterogeneous attributes.

C. Scenario 3 – Mixed Attribute

The objective of the third experiment is to measure the performance of MOACS for mixed homogeneous and heterogeneous group formation. MOACS is used for group formation in a Software Analysis and Design (APPL) class with 38 students using heterogeneous and homogeneous attributes. The main task of the APPL class is document analysis and design. The attributes used are learning style in sensing/intuitive dimension (LSSI) set to homogeneous and learning style in active/reflective dimension (LSAR) and previous knowledge level (KL) set to heterogeneous. The size of the group was four. The result of grouping is shown in the following chart.

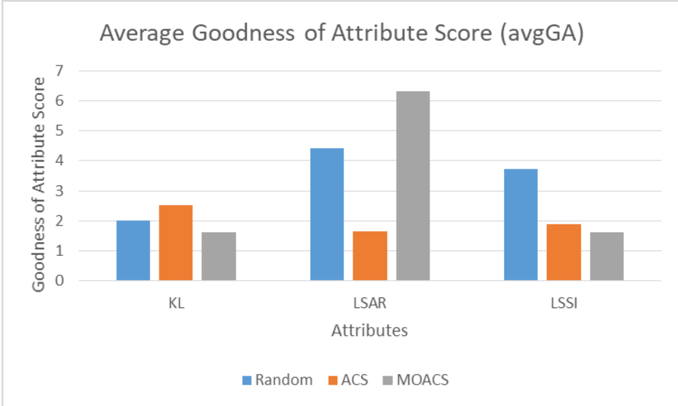

Figure 6 Average Goodness of Attribute Score in Scenario 3

Figure 6 shows that MOACS is able to maximize Learning Style in Active/Reflective dimension (LSAR) and minimize Learning Style in Sensing/Intuitive dimension (LSSI) attributes. The learning style in active/reflective dimension (LSAR) gives maximum avgGA, which means that it is good for heterogeneous attributes. On the other hand, learning style in sensing/intuitive dimension (LSSI) gives a minimum avgGA, which means that it is good for homogeneous attributes. The knowledge level score has range between 4, 3.5, 3, 2.5, 2 until 1 before it is normalized to 0-1. The score variation for each learner is low, thus making it difficult to gain maximum goodness of attribute score. LSAR score has range between -11 to 11 before it is normalized to 0-1. The score variation for each learner tends to give a maximum goodness of attribute score for heterogeneous attribute. Similar to LSAR, LSSI score has range between -11 to 11, then it is normalized to 0-1. The score variation for each learner tends to give s minimum goodness of attribute score for homogeneous attributes.

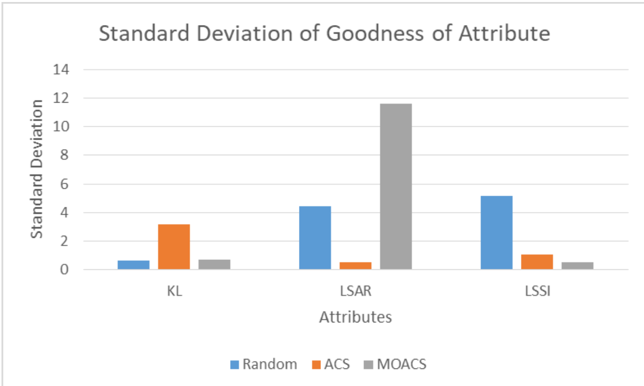

Figure 7 Standard Deviation of Goodness of Attribute in Scenario 3

Figure 7 shows that MOACS is able to minimize the distribution of Knowledge Level (KL) and Learning Style in Sensing/Intuitive dimension (LSSI) in group results. The result indicates that MOACS is able to distribute members among groups with balanced knowledge level and learning style in sensing intuitive attribute scores. The expected results of group formation using mixed attributes are maximum avgGA for heterogeneous attributes, minimum avgGA for homogeneous attributes, and minimum stdGA for all attributes. Based on the average goodness of attributes in Figure 6 and standard deviation in Figure 7, the MOACS is appropriate for group formation using mixed attributes.

The experiment results show that MOACS gives minimum avgGA and stdGA in homogeneous group formation, which means that the group has member with similar degrees of attributes. The good result is shown in mixed group formation in two of three attributes related to avgGA. MOACS gives a maximum avgGA in learning style in active/reflective dimension for heterogeneous attribute and a minimum avgGA in learning style in sensing/intuitive dimension for homogeneous attribute. Furthermore, it gives a minimum stdGA in knowledge level and learning style in sensing/intuitive dimension. On the other hand, MOACS gives minimum avgGA and stdGA in heterogeneous group formation, which means MOACS is able to distribute members among groups with balanced attribute scores, but does not result in good goodness of attribute score for heterogeneous attributes. To conclude, MOACS is appropriate for group formation using mixed attributes.

V. CONCLUSION

We have implemented Multi Objective Ant Colony System (MOACS) for group formation. The group formation is dynamic which can be applied to various combinations of attributes. Attributes that can be used in group formation includes learning styles, thinking styles, interests, and learner's knowledge. Considering collaborative learning requires homogeneous groups for some tasks or heterogeneous groups for other cases, we classify learners' attributes into homogeneous or heterogeneous. We test MOACS for homogeneous, heterogeneous, and mixed group formation. The tests show that MOACS is appropriate for homogeneous or mixed group formation.

REFERENCES

[1] V. Yannibelli and A. Amandi, "A deterministic crowding evolutionary algorithm to form learning teams in a collborative learning context.," *Expert Systems with Applications, 39(10), 8584-8592,* 2012.

[2] D. Dansereau and D. Johnson, "Cooperative Learning," *In : Druckman, D., Bjork, R.A. : Learning, Remembering, Believing: Enhancing Human Performance, National Academic Press, Washington, D.C.,* pp. 83-111, 1988.

[3] D. Johnson and R. Johnson, Leading the Cooperative School, Edina, MN, 1989.

[4] R. Slavin, "When Does Cooperative Learning Increase Achievement?," *Psychological Bulletin, Vol. 94 (1983),* pp. 429-445.

[5] I. Magnisalis, S. Demetriadis and A. Karakostas, "Adaptive and Intelligent Systems for Collaborative Learning Support : A Review of the Field," *IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES,* vol. 4, 2011.

[6] P. Dillenbourg, "What do you Mean by Collaborative Learning?," *Collaborative Learning: Cognitive and Computational Approaches, Elsevier Science,* pp. 1-19, 1999.

[7] A. Owens, E. A. Mannix and M. A. Neale, "Strategic formation of groups: Issues in task-performance and team member selection.," *In D. H. Gruenfeld, editor, Research on managing groups and teams: Composisition,* vol. 1, pp. 149-165, JAI PRESS, 1998.

[8] A. Ounnas, Enhancing the automation of forming groups for education with semantics (PhD dissertation), University of Southampton, 2010.

[9] H. U. Hoppe, "Use of multiple student modeling to parameterize group learning," 1995.

[10] A. Inaba, T. Supnithi, M. Ikeda, R. Mizoguchi and J. Toyoda, "How Can We Form Effective Collaborative Learning Groups?," 2000.

[11] L. K. Soh, N. Khandaker, X. Liu and H. Jiang, "A Computer-Supported Cooperative Learning System with Multiagent Intelligence," 2006.

[12] M. A. Redmond, "A computer program to aid assignment of student project groups," 2001.

[13] D.-Y. Wang, S. S. Lin and C.-T. Sun, "DIANA : A computer-supported heterogeneous grouping system for teachers to conduct successful small learning groups," 2007.

[14] R. Cavanaugh, M. Ellis, R. Layton and M. Ardis, "Automating the process of assigning students to cooperative-learning teams," *AGE,* vol. 9, p. 1, 2004.

[15] C. E. Christodoulopoulos and K. A. Papinikolaou, "A Group Formation Tool in an E-Learning Context," 2007.

[16] S. Graf and R. Bekele, "Forming Heterogeneous Groups for Intelligent Collaborative Learning Systems with Ant Colony Optimization," *In Proceedings of Intelligent Tutoring Systems,* pp. 217-226, 2006.

[17] Alfonseca, "The Impact of Learning Styles on Student Grouping for Collaborative Learning: A Case Study," *User Modeling and User Adapted Interaction,* vol. 16, pp. 377-401, 2006.

[18] P. Paredes, "The Application of Learning Styles in Both Individual and Collaborative Learning," *Proc. Sixth IEEE Int'l Conf. Advanced Learning Technologies,* pp. 1141-1142, 2006.

[19] A. Gogoulou, E. Gouli, G. Boas, E. Liakou and M. Grigoriadou, "Forming homogeneous, heterogeneous and mixed groups of learners," *In P. Brusilovsky, M. Grigoriadou, K. Papanikolaou (Eds.), Proceeding of workshop on personalization in learning environments at individual and group level in conjunction with the 11th international conference on user modeling (pp. 33-40). Corfu, Greece.,* 2007.

[20] R. Bekele, "Computer-assisted learner group formation based on personality traits (PhD dissertation)," *Hamburg University,* 2005.

[21] S. L. Pierzon, "Social loafing and free riding in online learning groups," *PhD Dissertation,* 2011.

[22] N. Herrmann, "Creativity, learning, and the specialized brain in the context of education for gifted and talented children.," *Adapted from an address to the 7th world conference on gifted and talented children, Sal Lake City, Utah,* 1987.

[23] S. Liu, M. Joy and N. Griffith, "An Exploratory Study on Group Formation Based on Learning Style," *2013 IEEE 13th International Conference on Advanced Learning Technologies.*

[24] R. M. Felder and L. K. Silverman, "Learning and teaching style in engineering education," *Engineering education 78.7 (1988),* pp. 674-681.

[25] M. Kyprianidou, S. Demetriadis, T. Tsiatsos and A. Pombortsis, "Group formation based on learning styles: can it improve students' teamwork?," *Educational Technology Research and Development,* Vols. 60(1), 83-110, 2012.

[26] R. Hubscher, "Assigning students to groups using general and context-specific criteria.," *IEEE Transactions on Learning Technologies, 3(3), 178-189.,* 2010.

[27] M. I. Dascalu, C. N. Bodea, M. Lytras, P. O. de Pablos and A. Burlacu, "Improving E-learning Communities Through Optimal Composition of Multidisciplinary Learning Groups," *Computer in Human Behavior,* vol. 30, pp. 362-371, 2014.

[28] B. Baran and M. Schaerer, "A Multiobjective Ant Colony System for Vehicle Routing Problem with Time Windows. In," *Applied Informatics,* pp. 97-102, 2003.

[29] L. Wang, J. Shen and J. Luo, "Multi-objective ant colony system for data-intensive service provision," in *Advanced Cloud and Big Data (CBD), 2014 Second International Conference on (pp. 45-52). IEEE*, 2014.