**TELKOMNIKA Telecommunication, Computing, Electronics and Control**
Vol. 18, No. 1, February 2020, pp. 199~207
ISSN: 1693-6930, accredited First Grade by Kemenristekdikti, Decree No: 21/E/KPT/2018
DOI: 10.12928/TELKOMNIKA.v18i1.14922


# Development of online learning groups based on MBTI learning style and fuzzy algorithm

**Budi Laksono Putro, Yusep Rosmansyah, Suhardi**
School of Electrical Engineering and Informatics, Bandung Institute of Technology, Bandung, Indonesia

**Article Info**

***Article history:***

Received Aug 30, 2019
Revised Nov 29, 2019
Accepted Dec 21, 2019

***Keywords:***

21st century skills
Collaborative problem solving
Digital learning environment
Group development
Intelligent agent

**ABSTRACT**

Group development is an initial step and an important influence on learning collaborative problem solving (CPS) based on the digital learning environment (DLE). Group development based on the Myers-Briggs types indicators (MBTI) rule proved successful for the educational and industrial environment. The MBTI ideal group rules are reached when a group leader has the highest level of leadership and compatibility between group members. The level of leadership and suitability of group members is determined based on the MBTI learning style (LS). Problems arise when the population of MBTI LS with the highest level of leadership is over. This will lead to dual leadership problems and have an impact on group disharmony. This study proposes an intelligent agent software for the development of the ideal group of MBTI, using the Fuzzy algorithm. The intelligent agent was developed on the SKACI platform. SKACI is a DLE for CPS learning. Fuzzy algorithm for solving dual leadership problems in a group. Fuzzy algorithm is used to increase the population of MBTI LS to 3 levels, namely low, medium and high. Increasing the population of MBTI LS can increase the probability of forming an ideal group of MBTI. Intelligent agents are tested based on a quantitative analysis between experimental classes (applying intelligent agents), and control classes (without intelligent agents). Experiment results show an increase in performance and productivity is better in the experimental class than in the control class. It was concluded that the development of intelligent agents had a positive impact on group development based on the MBTI LS.



***Corresponding Author:***

Budi Laksono Putro,
School of Electrical Engineering and Informatics,
Bandung Institute of Technology,
Bandung, Indonesia.
Email: blputro@gmail.com

## 1. INTRODUCTION

Collaborative problem solving (CPS) learning based on digital learning environment (DLE) is an effort to realize 21st century skills [1-6]. Group development is a first step and significant influence on the effectiveness of CPS learning based on DLE [4, 7-13]. There are many alternative methods for developing groups, and each alternative method of group formation has advantages and disadvantages [14]. The criteria of the best group are as follows: (1) appropriate individual composition, (2) each individual plays a good function, (3) increased individual productivity, (4) increased group productivity, and (5) enjoyable learning experiences for both individuals and as a group [14].

Group development based on the Myers-Briggs types indicators rule (MBTI) has proven successful for the educational and industrial environment [14]. The MBTI ideal group rule is reached when a group leader has the highest level of leadership and compatibility between group members. The level of leadership and suitability of group members is determined based on the MBTI learning style (LS). Problems arise when the population of MBTI LS with the highest level of leadership is over. This will lead to dual leadership problems and have an impact on group disharmony. There is no intelligent agent research for group development that addresses the issue of the possibility of dual leardership in MBTI.

This study proposes an intelligent agent software for the development of the ideal group of MBTI, using the Fuzzy algorithm. The intelligent agent was developed on the SKACI platform. SKACI is a DLE for CPS learning. The use of fuzzy algorithms to solve the problem of dual leadership. Fuzzy clustering method to create homogenous clusters based on weighting the specified criteria [15-18]. The dual leadership problem is solved by grouping each level of leadership into several homogeneous cluster levels [12, 15]. Each level of leadership of the MBTI LS is made into a homogeneous cluster based on high, medium, and low levels. The MBTI LS leadership level was originally 4 (four) levels, with a fuzzy algorithm clustering into 12 (twelve) levels. Increasing the level of leadership of the MBTI LS can increase the probability of forming an ideal group of MBTI.

The intelligent agent development method for group development uses constraint programming (CP) modeling [19, 20] namely flowchart diagrams, and PHP programming scripts. The intelligent agent test is based on the intelligent agent performance metric for group development on CPS learning. The performance metrics are based on 5 (five) measuring tools namely [21, 22]: Group formation time, optimization of student distribution to groups, Collaboration performance (CO), Knowledge, and skills. It is hoped that the implementation of intelligent agents can increase the efficiency of group formation time, group performance, and increase the productivity of CPS learning (knowledge, skills). Intelligent agent testing based on quantitative analysis comparison between experimental class (applying intelligent agent), and control class (without an intelligent agent). Improved performance and productivity of CPS learning in the experimental class is better than the control class. It was concluded that the development of intelligent agents had a positive impact on group development based on the MBTI LS.

This paper consists of 4 Sections. Background research, issues, goal setting, and general overview are explained in section 1; research method research is discussed in section 2; section 3 discusses results and analysis; development of intelligent agents on the SKACI platform is discussed in section 3.1; experiments and analyzes of intelligent agents for group development CPS learning on the SKACI platform are discussed in section 3.2; and conclusions and suggestions research opportunities are further discussed in section 4.

## 2. RESEARCH METHOD

This chapter discusses research methodology which consists of stages of research and detailed steps of each stage of research. This research consists of 2 main stages, namely:

- Development of intelligent agents for group formation based on MBTI LS, and fuzzy algorithms. Intelligent agents are developed on the SKACI platform. SKACI is a DLE for CPS learning. The output is an intelligent agent for group development based on the MBTI LS and fuzzy algorithms.
- Analysis of the performance of intelligent agents for group development on CPS learning on the SKACI platform.

### 2.1. Intelligent agent for group development

The development of intelligent agents on the SKACI platform [23, 24] is illustrated in Figure 1. SKACI is a DLE for CPS learning. SKACI functionalities include individual learning environments [25], and collaborative learning environments or often referred to as Computer-supported collaborative learning (CSCL) [23, 26, 27]. Development of intelligent agents for group development using constraint programming (CP) modeling [19, 20] namely flowchart diagrams and PHP programming scripts. The stages of the framework for developing intelligent agents forming groups on the SKACI platform are: (a) SLE-interface, (b) group formation-intelligent agent, (c) Collaborative problem solving (CPS)-Activity.

SLE-interface in Figure 1 part (a) as a CPS learning interface for student profile, questionnaire (MBTI learning style), and course assignment. The intelligent agent implementation on the SKACI platform in Figure 1 part (b). This stage consists of 3 (three) main functionalities, namely: (1) Classifying and Ranking of MBTI LS Attributes, (2) Increasing LS of MBTI Population with Fuzzy Algorithm, and (3) Group formation algorithms based on MBTI team leader rules. Measurement of the effectiveness of intelligent agents forming groups in Figure 1 part (b), namely: the efficiency of group formation time, and optimizing the distribution of students in groups.

CPS learning on the SKACI Platform is illustrated in Figure 1 part (c) [28]. The stages of CPS learning activities include (1) collaborative learning, and (2) individual learning. The performance of group formation on CPS learning is measured by individual learning outcomes and collaborative learning. DLE-based CPS learning is an effort to realize 21st century skills (21st century Skill) [2]. 21st century skills are the skills needed to deal with 21st century problems [2].

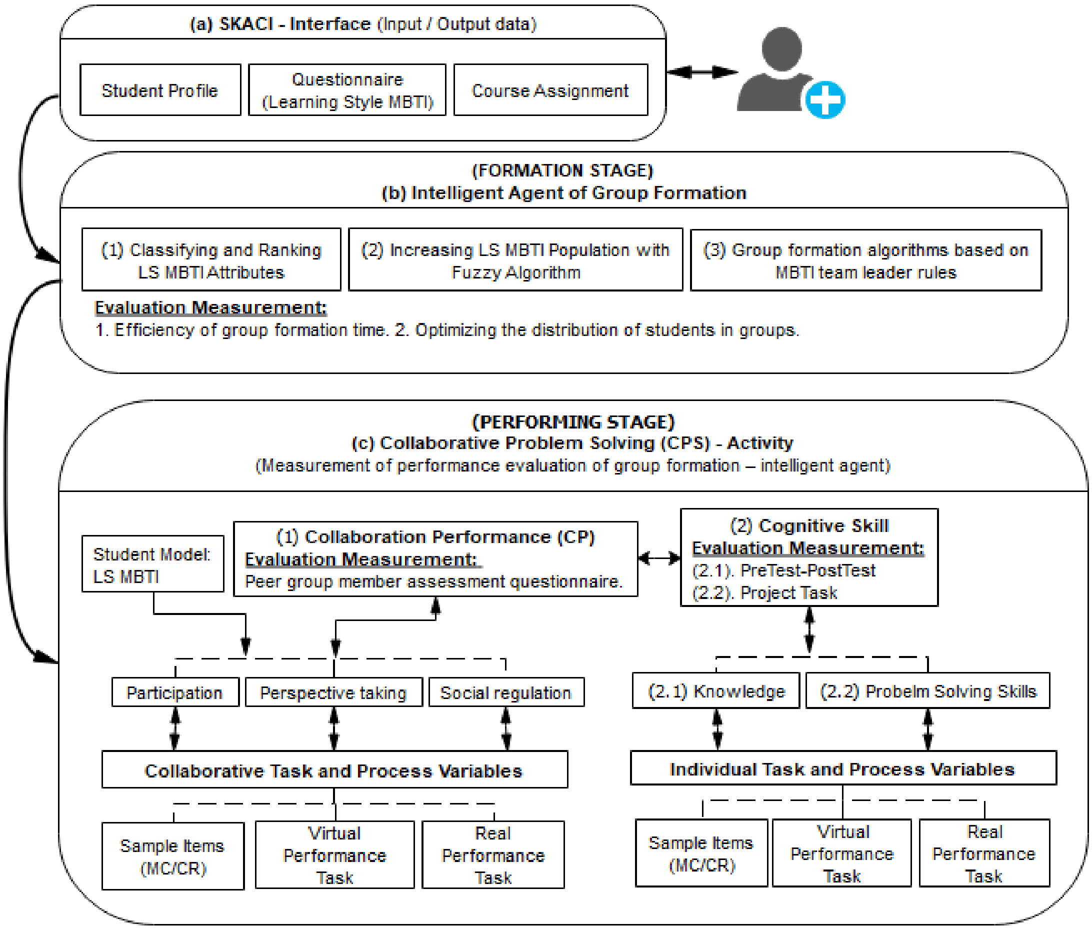


Figure 1. Intelligent agents for the development of CPS learning groups on the SKACI platform [2, 11, 29]

## 2.2. Intelligent agent performance metrics

Intelligent agent performance measurement based on measurement metrics in Table 1. Intelligent agent performance metrics consist [21, 22]**:** group formation time, optimization of student distribution to groups, collaboration performance (CO), knowledge, and skills. Measurement of group formation time and optimization of student distribution in groups is carried out at the formation stage. Collaboration performance (CO), knowledge, and skill measurements are performed at the performing stage [2, 11, 29].

Quantitative analysis of intelligent agents based on comparison of performance measurements between the experimental class (applying intelligent agents) and the control class (without applying intelligent agents) on CPS learning. The implementation of intelligent agents is successful when the results of the experimental class (applying intelligent agents) measurement are better than the control class (without applying intelligent agents).

Table 1. Metrics performance of intelligent agents for group development on CPS learning

| Stage of group formation | Metrics performance of group formation [21, 22] | Measurement | Student | Group | Class |
|---|---|---|---|---|---|
| Formation Stage | Group formation time | Efficiency time | | √ | √ |
| | optimization of student distribution in groups | Percentage of student distribution | | √ | √ |
| Performing Stage | Collaboration performance (CO) | Peer group member assessment questionnaire. | √ | √ | √ |
| | Knowledge | Pre-Test & Post-Test | √ | √ | √ |
| | Skills | Project task | √ | √ | √ |

## 3. RESULTS AND ANALYSIS

This chapter discusses the development of intelligent agents for group development on the SKACI platform in chapter 3.1, and the Analysis of Intelligent agent Implementation in chapter 3.2. The steps for developing an intelligent agent for group development are illustrated in Figure 2.

### 3.1. Intelligent agent for group development

The process stages of intelligent agent software for group development are depicted in Figure 2. Intelligent agents for group development are implemented at the formation Stage, in Figure 1 part (b). Intelligent agents for group development consist of 3 (three) main functional groups, namely: (1) classifying and ranking of MBTI LS attributes, (2) increasing LS MBTI Population with fuzzy algorithm, and (3) group formation algorithms based on MBTI rules. A detailed explanation of each section is explained in the sub-chapter below.

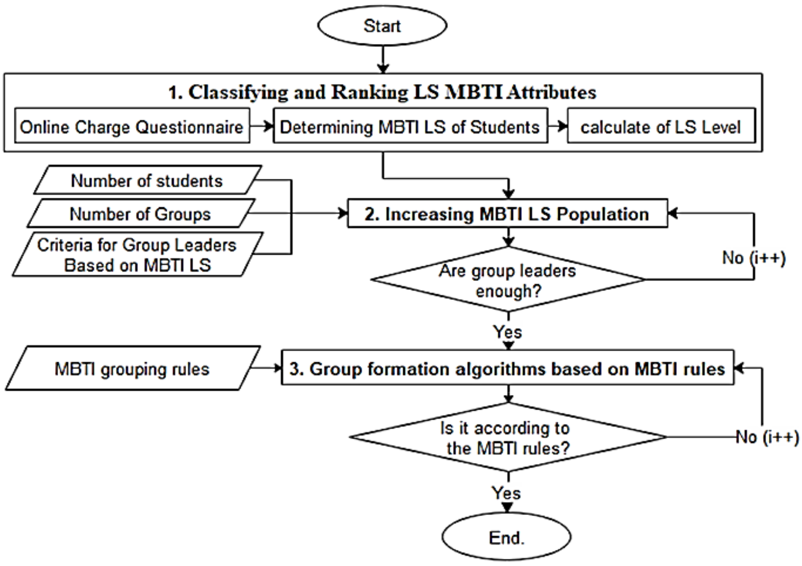


Figure 2. Process flow of Intelligent agent software

#### 3.1.1. Classifying and ranking LS MBTI attributes

The MBTI LS data was obtained by using the online questionnaire on the SKACI interface. Classifying and ranking MBTI LS is the first step to sort the highest level of leadership to the lowest [14]. The MBTI LS leadership level is depicted in Table 2. Tier 0 is the highest leadership level, and tier 4 is the lowest leadership level. The MBTI LS classification algorithm process is illustrated in Figure 3. The purpose of this stage is to rank leadership from highest to lowest. The highest level of leadership is a priority for candidates to become group leaders.

```
$ls-mbti = [E => , I => , S => , N => , T => , F => , J => , P => ];
$ls-mbtiCount = array_count_values($_POST);

foreach ($ls-mbtiCount as $key => $value)
{ $ls-mbti[$key] = $value; }

$characteristics = ; $membership = 0;
if ($ls-mbti[E] > $ls-mbti[I]) { $characteristics .= E; $membership += $ls-mbti[E]; } else { $characteristics .= I; $membership +=
$ls-mbti[I];}
if ($ls-mbti[S] > $ls-mbti[N]) { $characteristics .= S; $membership += $ls-mbti[S]; } else { $characteristics .= N; $membership +=
$ls-mbti[N]; }
if ($ls-mbti[T] > $ls-mbti[F]) { $characteristics .= T; $membership += $ls-mbti[T]; } else { $characteristics .= F; $membership +=
$ls-mbti[F]; }
if ($ls-mbti[J] > $ls-mbti[P]) { $characteristics .= J; $membership += $ls-mbti[J]; } else { $characteristics .= P; $membership +=
$ls-mbti[P]; }
$fuzzy = $membership/70; $score_membership = ;
```

Figure 3. Classifying and ranking of MBTI LS

### 3.1.2. Increasing LS MBTI population with fuzzy algorithm

An increased population of LS MBTI for solutions to dual leadership problems in group development. An increased population of LS MBTI using the fuzzy algorithm. The determination of the group leader using the MBTI rules is illustrated in Table 3. Increasing the number of MBTI LS populations using fuzzy algorithms, illustrated in Figure 4. Utilization of fuzzy algorithms by creating 3 levels of MBTI LS levels: 1 (high), 2 (medium) and 3 (low). The population level of LS MBTI with the application of the fuzzy algorithm to 15 levels as shown in Table 3, increasing the chances for the formation of the composition of the CPS learning group.

The first step is to determine the number of group leaders. The group leader is chosen based on the highest leadership priority (Tier 0 or tier 1). Tier 0 (ESTJ, xor, ISTJ) is the priority to become a group leader and may not have group members with the same leadership level (Tier 0 ie ESTJ, xor ISTJ). Tier 1 (INTJ, xor ENTJ) is the second priority for being a group leader and may not have group members with higher or equal leadership levels.

Table 2. MBTI team leader role [14]

| Team Leader Role | Guardians | Artisans | Idealists | Rationals |
|---|---|---|---|---|
| Tier 0 | ISTJ, ESTJ | | | |
| Tier 1 | | ISTP, ESTP | | InTJ, InTP, EnTP, EnTJ |
| Tier 2 | ISFJ, ESFJ | | InFP, EnFP | |
| Tier 3 | | | InFJ, EnFJ | |
| Tier 4 | | ISFP, ESFP | | |

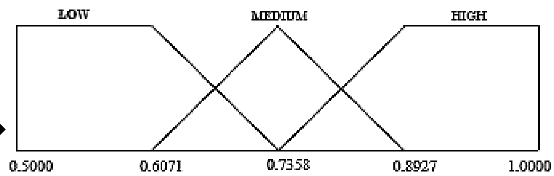


Figure 4. Increased population of LS MBTI using fuzzy algorithm

Table 3. Increased population of MBTI LS

| Level | Guardians | Artisans | Idealists | Rationals |
|---|---|---|---|---|
| 1 | ISTJ, ESTJ | | | |
| 2 | ISTJ, ESTJ | | | |
| 3 | ISTJ, ESTJ | | | |
| 1 | | ISTP, ESTP | | InTJ, InTP, EnTP, EnTJ |
| 2 | | ISTP, ESTP | | InTJ, InTP, EnTP, EnTJ |
| 3 | | ISTP, ESTP | | InTJ, InTP, EnTP, EnTJ |
| 1 | ISFJ, ESFJ | | InFP, EnFP | |
| 2 | ISFJ, ESFJ | | InFP, EnFP | |
| 3 | ISFJ, ESFJ | | InFP, EnFP | |
| 1 | | | InFJ, EnFJ | |
| 2 | | | InFJ, EnFJ | |
| 3 | | | InFJ, EnFJ | |
| 1 | | ISFP, ESFP | | |
| 2 | | ISFP, ESFP | | |
| 3 | | ISFP, ESFP | | |

### 3.1.3. Group formation algorithms based on MBTI rules

Group formation algorithms based on MBTI rules are rules of group development based on the level of leadership of MBTI LS, and rules of compatibility between group members based on MBTI LS [14]. Stages of student distribution in groups based on the MBTI enneagram matrix is to determine the number of group leaders, and the distribution of group members.

### 3.2. Analysis of implementation of intelligent agent

Analysis of intelligent agent implementation is based on a comparison between the experimental class (applying intelligent agent), and the control class (without intelligent agent). The objects of this study were -2 classes of Database of 2016 Computer Science Education study programs at UPI. One experimental class and one control class, and each class consists of 36 students. Each class is made up of 9 groups for each group of 4 people. Data processing using IBM SPSS Statistics software.

The group formation of each class is static and is done once at the beginning of CPS learning. Testing of intelligent agents for group formation using statistical methods paired Sample T-Test that compares groups between the experimental class and the control class. Quantitative analysis of intelligent agents forming groups based on the performance of intelligent agents in Table 1. The results of the performance of intelligent agents for group formation based on 5 (five) metric measurements are [21, 22]:

#### 3.2.1. Group formation time

The effectiveness of group formation time is compared between the experimental class and the control class. The measurement of group formation time is illustrated in Table 4. The time for the experimental class is 15 minutes, and the control class is 27 minutes. Uneven group composition occurs in the control class, so it is necessary to re-form the group. Whereas in the experimental class group formation is only done once.

Table 4. Group formation time

| Experiment class | | Control Class | |
|---|---|---|---|
| Component of group formation time | Quantity | Component of group formation time | Quantity |
| Online questionnaire MBTI | 15 minutes | Negotiation between students | 15 minutes |
| Processing of LS MBTI | 0.564 seconds | Group formation | 12 minutes |
| Group formation by intelligent agent | 0.596 seconds | | |
| Total Time | 15 minutes, 1,133 seconds. | Total Time | 27 minutes |

#### 3.2.2. Optimizing the distribution of students in groups

Optimizing the distribution of students in groups for the experimental class is 100%, while for the control class is 90%. The class experiment is more optimal because of the certainty of the group development rules of the MBTI. While the control class leaves 10% of students who haven't gotten a group, this is due to the individual match factor between students. A renegotiation process is needed to distribute the remaining 10% of students.

#### 3.2.3. Collaboration performance (CP)

Collaboration performance (CP) is measured by peer assessment online between members in one group. CP is done every time after working on a collaborative project and is done 3 times. The questionnaire aims to find out three CP values, namely: participation, perspective thinking, and social regulation. The average CP value in experiment class and control class is illustrated in Figure 5. CP value in experiment class is better than control class. Group collaboration in the experimental class is better than the control class. Group composition based on MBTI rules has proven to be able to increase group collaboration.

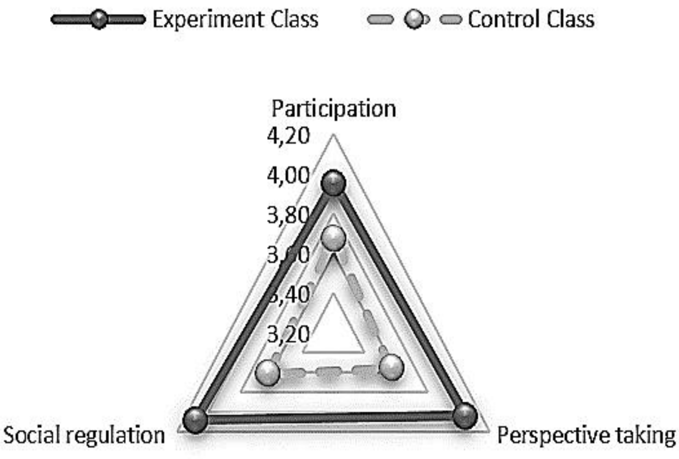


Figure 5. Collaborative performance (CO)

#### 3.2.4. Knowledge

Knowledge is taken from the average score of the pre-test and post-test for each student conducted online on the SKACI platform. The comparison of pre-test and post-test values between the experimental class and the control class is illustrated in Figure 6. The average value in the experimental class is better than the control class. The suitability of individuals in groups is proven to increase group collaboration and knowledge of each individual.

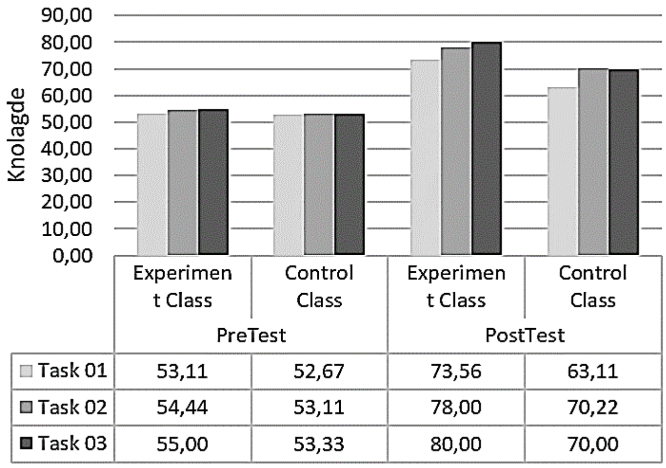


Figure 6. Knowledge value of CPS learning

### 3.2.5. Skill

Skills are taken from the value of student project assignments as a group. Project tasks are performed 3 times either in the experiment class or in the control class. Good group collaboration will affect the quality of project tasks for each group. The average skill score in the experimental class is better than the control class, shown in Figure 7. The skill value in the experimental class is strongly influenced by good group collaboration.

The results of the experiment based on performance metrics on intelligent agents for group development show that the experimental class is more effective than the control class. The application of intelligent agents for group development based on MBTI rules has a positive effect on group collaboration. Increased group collaboration has a positive effect on the value of skills and knowledge both for individuals and groups.

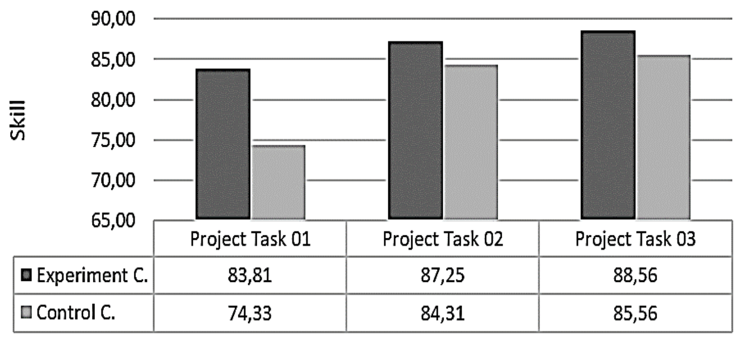


Figure 7. Skills in CPS learning

## 4. CONCLUSION

Group development based on MBTI rules has proven successful for the education and industry environment. MBTI ideal group rules are achieved when a group leader with the highest level of leadership, and compatibility between group members. The level of leadership and suitability of group members is determined based on the MBTI LS. Problems arise when the population of MBTI LS with the highest level of leadership is over. This will lead to dual leadership problems and have an impact on group disharmony. This study proposes an intelligent agent software for the development of the ideal group of MBTI, using the fuzzy algorithm. Fuzzy algorithm for solving dual leadership problems in a group. Fuzzy algorithm is used to increase the population of MBTI LS to 3 levels, namely low, medium, and high. Increasing the population of MBTI LS can increase the probability of forming an ideal group of MBTI.

Intelligent agent is successful in solving dual leadership problems. The test results in the experimental class (applying intelligent agents) are better than the control class (without intelligent agents). Intelligent agent performance measurement based on 5 (five) measurement metrics, namely: group formation time, optimization of student distribution to groups, collaboration performance (CO), knowledge, and skills. It was concluded that the development of intelligent agents had a positive effect for group development based on the MBTI LS.

## ACKNOWLEDGEMENTS
Praise Allah for all the blessings that He has given. Thanks also to our parents, wife, children and friends for their participation and support, and to the Indonesian Ministry of Education and Finance Ministry for the funding of the BUDI-DN scholarship.

## REFERENCES
[1] M. E. Webb et al., "Challenges for IT-Enabled Formative Assessment of Complex 21st Century Skills," *Technol. Knowl. Learn.*, vol. 23, no. 3, pp. 441–456, Aug 2018.
[2] P. Griffin and E. Care, "Assessment and teaching of 21st century skills," *Br. J. Educ. Technol.*, vol. 46, no. 4, pp. E15–E16, 2015.
[3] J. Khlaisang and N. Songkram, "Designing a Virtual Learning Environment System for Teaching Twenty-First Century Skills to Higher Education Students in ASEAN," *Technol. Knowl. Learn.*, vol. 24, no.1, pp. 41-63, 2019.
[4] A. Triayudi and I. Fitri, "A new agglomerative hierarchical clustering to model student activity in online learning," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 17, no. 3, pp. 1226-1235, June 2019.
[5] Rasim Rasim, Y. Rosmansyah, A. Z. R. Langi, and Munir Munir, "Selection of Learning Materials Based on Students' Behaviors in 3DMUVLE," *TELKOMNIKA Telecommunication Computing Electronics and Control,* vol. 16, no. 5, pp. 2127–2136, 2018.
[6] T. Oktavia, H. L. H. S. Warnars, and S. Adi, "Conceptual Model of Knowledge Management and Social Media to Support Learning Process in Higher Education Institution," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 15, no. 2, pp. 678-685, June 2017.
[7] S. Isotani, A. Inaba, M. Ikeda, and R. Mizoguchi, "An ontology engineering approach to the realization of theory-driven group formation," *Int. J. Comput. Collab. Learn.*, vol. 4, no. 4, pp. 445–478, Aug. 2009.
[8] N. Maqtary, A. Mohsen, and K. Bechkoum, "Group Formation Techniques in Computer-Supported Collaborative Learning: A Systematic Literature Review," *Technol. Knowl. Learn.*, vol. 24, no. 2, pp. 1–22, June 2019.
[9] I. Srba and M. Bielikova, "Dynamic Group Formation as an Approach to Collaborative Learning Support," in *IEEE Transactions on Learning Technologies*, vol. 8, no. 2, pp. 173-186, 1 April-June 2015.
[10] R. C. D. Reis, S. Isotani, C. L. Rodriguez, K. T. Lyra, P. A. Jaques, and I. I. Bittencourt, "Affective states in computer-supported collaborative learning: Studying the past to drive the future," *Comput. Educ.*, vol. 120, no. May, pp. 29–50, 2018.
[11] A. A. von Davier, J. Hao, L. Liu, and P. Kyllonen, "Interdisciplinary research agenda in support of assessment of collaborative problem solving: lessons learned from developing a Collaborative Science Assessment Prototype," *Comput. Human Behav.*, vol. 76, pp. 631–640, November 2017.
[12] S. Lailiyah, E. Yulsilviana, and R. Andrea, "Clustering analysis of learning style on anggana high school student," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 17, no. 3, pp.1409-1416, June 2019.
[13] S. Mirzaei and A. F. Hayati, "Effects of the computer mediated communication interaction on vocabulary improvement," *TELKOMNIKA Telecommunication Computing Electronics and Control*, vol. 16, no. 5, pp. 2217–2225, 2018.
[14] S. T. Shen, S. D. Prior, A. S. White, and M. Karamanoglu, "Using personality type differences to form engineering design teams," *Eng. Educ.*, vol. 2, no. 2, pp. 54–66, 2007.
[15] D. Nurjanah, K. Dewanto, and F. D. Sari, "Homogeneous group formation in collaborative learning using fuzzy C-means," *2017 IEEE 6th International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, Hong Kong, no. 978, pp. 74–79, 2017.
[16] S. Ghosh and S. K. Dubey, "Comparative Analysis of K-Means and Fuzzy C-Means Algorithms," *Int. J. Adv. Comput. Sci. Appl.*, vol. 4, no. 4, pp. 35–39, May 2013.
[17] C. E. Christodoulopoulos and K. A. Papanikolaou, "A group formation tool in a E-Learning context," *19th IEEE International Conference on Tools with Artificial Intelligence (ICTAI 2007)*, Patras, pp. 117-123, 2007.
[18] Y. A. Pollalis and G. Mavrommatis, "Using similarity measures for collaborating groups formation: A model for distance learning environments," *Eur. J. Oper. Res.*, vol. 193, no. 2, pp. 626–636, Mar 2009.
[19] Krzysztof Apt, "Principles of constraint programming," Cambridge: Cambridge University Press, 2003.
[20] F. Rossi, P. Van Beek, and T. Walsh, "Handbook of Constraint Programming (Foundations of Artificial Intelligence)," 2006.
[21] A. Ounnas, D. E. Millard, and H. C. Davis, "A metrics framework for evaluating group formation," *Proceedings of the 2007 international ACM conference on Supporting group work*, pp. 221–224, Nov. 2007.
[22] I. Wu and W. Chen, "Evaluating the e-learning platform from the perspective of knowledge management: The AHP approach," *J. Libr. Inf. Stud.*, vol. 11, no. 1, pp. 1–24, June 2013.
[23] G. Stahl, T. Koschmann, and D. Suthers, "Computer-supported collaborative learning: An historical perspective," Cambridge Handb. Learn. Sci., pp. 409–426, Jan 2006.

[24] K. H. Allehaibi and N. N. Albaqami, “A Unified Quality Control Model for E-Learning Systems,” *Int. J. Electr. Comput. Eng.*, vol. 7, no. 3, pp. 1355–1366, June 2017.
[25] A. Hidayat and V. G. Utomo, “Adaptive Online Module Prototype for Learning Unified Modelling Language (UML),” *Int. J. Electr. Comput. Eng.*, vol. 6, no. 6, pp. 2931–2938, December 2016.
[26] P. Tchounikine, N. Rummel, and B. M. McLaren, “Computer Supported Collaborative Learning and Intelligent Tutoring Systems,” *Adv. Intell. Tutoring Syst.*, pp. 447–463, 2010.
[27] M. R. M. Veeramanickam and N. Radhika, “A Smart E-Learning System for Social Networking,” *Int. J. Electr. Comput.* Eng., vol. 4, no. 3, pp. 447–455, June 2014.
[28] P. Griffin, “Assessing collaborative problem solving," [Online], Available: https://insegnantiduepuntozero.files.wordpress.com/2017/01/assessing-collaborative-problemsolving_p_griffin.pdf, 2017.
[29] F. Koch and D. B. Eds, "Advances in Social Computing and Multiagent Systems," *6th International Workshop on Collaborative Agents Research and Development, CARE 2015 and Second International Workshop on Multiagent Foundations of Social Computing, MFSC 2015*, vol. 541, May 2015.

## BIOGRAPHIES OF AUTHORS

**Budi Laksono Putro** received his bachelor degree in computer science from Universitas Padjadjaran, Bandung, Indonesia, in 2002, and his master degree at the School of Electrical Engineering and Informatics (STEI), ITB, Bandung, Indonesia, in 2010. He is currently working toward a doctoral degree at the School of Electrical Engineering and Informatics, ITB. He works for Indonesia University of Education in the Computer Science Education field. He is currently a member of the Services Computing Research Group (SCRG) of SEEI ITB. His current research interest includes mobile learning technologies, service computing, software engineering, and information systems.

**Yusep Rosmansyah** received the B.S. degree from Bandung Institute of Technology, Indonesia, in 1993, and both the M.Sc. and Ph.D. degrees from the University of Surrey, U.K. He has been a researcher and an associate professor at the School of Electrical Engineering and Informatics, Bandung Institute of Technology (SEEI ITB), Indonesia. His current research interest includes mobile learning technologies and cyber security.

**Suhardi** received the bachelor degree in electrical engineering from the Bandung Institute of Technology, Bandung, Indonesia, in 1988, the master degree in management from Parahyangan Catholic University, Bandung, Indonesia, in 2012, and the Doctor of Engineering degree in telecommunication engineering from the Technical University of Berlin, Berlin, Germany, in 1997. He is currently an Associate Professor with the School of Electrical Engineering and Informatics, SEEI ITB. He is the Head of Services Computing Research Group (SCRG), SEEI ITB. His research interests include service computing, IT value and risk, service systems engineering, information and social networks, information and social networks, information governance and management, and internet society and law.