Team Formation with Diversity and Similarity Goals

Marco Chiarandini[1] [0000−0002−6136−8496] and Zhiru Sun[2] [0000−0002−9028−5905]

[1] Department of Mathematics and Computer Science
[2] Department of Design, Media, and Educational Science
University of Southern Denmark
{march,zhiru}@sdu.dk

Abstract. Collaborative learning has been widely used to foster students' communication skills and facilitate joint knowledge construction. However, there exists ongoing debate regarding the optimal formation of teams to maximize the development of these competencies. This work aims to provide educational managers and teachers with a practical tool for team formation, allowing for the control of member diversity *within* teams and similarity *across* teams based on pre-selected student characteristics. The tool takes input in the form of individual student assessments across various characteristics, alongside specifications for team size ranges. Additionally, for each characteristic of the students, it takes a definition of its order of importance and a diversity goal to achieve within the teams, that is, heterogeneity or homogeneity. The output is a distribution of students into teams that satisfies the specified sizes and optimizes diversity goals in the given order while promoting similarity across teams. The tool solves a lexicographic mixed integer linear programming problem. A notable feature of this approach is its ability to accommodate diversity criteria for both numerical and categorical characteristics. Through experimentation with six real-life cases involving up to 151 students per case, the tool demonstrates swift problem-solving capabilities using state-of-the-art solvers. This efficiency renders the tool readily applicable in practical educational settings.

Keywords: Team formation, Mixed integer linear programming, Lexicographic optimization.

1 Introduction

Collaborative learning is an effective method for engaging learners by facilitating communication and idea exchange among team members to construct knowledge together [10]. However, simply putting learners in teams does not guarantee the success of collaborative learning. Therefore, the classification of learners into well-functioning teams is one of the most challenging tasks in the field of collaborative learning. A line of research regarding team composition has categorized collaborative teams into two major types based on the *within*-team composition, which is *homogeneous team* (i.e., learners within a team having similar ability levels) and *heterogeneous team* (i.e., learners within a team having dissimilar ability levels) [13]. Various studies have compared the two types of teams on learners' achievement and social interaction and there seems to be a slight prevalence of the heterogeneous team as the best choice [13]. For example,researchers believe that, compared to homogeneous teams, learners in heterogeneous teams tend to coordinate and create common ground faster and easier because the diverse skills and characteristics of team members might be complementary to each other and to the team as a whole [11,12]. In addition, from the economics perspective, the level of equality or fairness in heterogeneous teams is higher than that in homogeneous teams because resources (e.g., time, knowledge) are more likely to be equally distributed to each team member instead of being collected by a single or limited number of team members [3].

In practice, three primary approaches are employed for team formation: *random grouping* (i.e., assigning learners in the teams by chance), *self-selected grouping* (i.e., the learners choose with whom they want to work), and *controlled grouping* (i.e., assigning learners in the teams by instructors or computing systems based on certain criteria) [1,6,2]. The random grouping method commonly lacks control over team homogeneity or heterogeneity, potentially leading to unequal participation and the formation of teams with varying characteristics. This can result in disparities among teams, fostering a sense of unfairness [7]. The self-selected grouping method tends to produce homogeneous teams characterized by shared interests and amicable relationships among members, albeit often leading to decreased task orientation and engagement in off-task behaviors [6]. The controlled grouping method addresses these issues by facilitating the creation of teams with desired levels of diversity or similarity *within* teams while also controlling for variation *among* teams. However, achieving these objectives complicates the assignment process both in terms of formalization and optimal solution finding. Consequently, research has increasingly focused on algorithmic approaches to achieve controlled team formation.

In the past decade, a variety of algorithm-based team formation methods has been proposed to form controlled teams, that is, to create teams that are as similar among themselves as possible (*inter-homogeneous*), while maximizing the learners' individual differences within such teams (*intra-heterogeneous*). The majority of team formation algorithms are based on population-based metaheuristics such as ant colony optimization [4], particle swarm optimization [9], and genetic algorithm [2]. Local search-based heuristics such as random restart hill-climbing [8] and variable neighborhood search are also employed to form collaborative teams [15]. There is no standard definition of the optimization criteria in these references. Perhaps the most flexible tool available is CATME [8], that allows instructors to define their own characteristics of interest, their weight of importance in the team formation and whether within-team similarity or dissimilarity should be promoted. Information about the pre-selected characteristics can be collected directly from the students using the web application built around the tool. Characteristics are handled by discretizing them. One interesting characteristic modeled in this way is the student-schedule compatibility to favor the creation of teams that can actually meet. CATME then assigns students to teams by maximizing the minimum of a compliance measure computed on each team. The assignment is found starting by a random assignment and improving it by swapping students in a hill climbing fashion. However, in studies that aim at assessing team creation policies (e.g., which characteristics are relevant to consider, whether they should be similar or dissimilar) finding heuristic solutions to the team formation problem is undesirable because it adds a confounding element to the analysis, namely, the unknown degree of approximation of the optimal solutions.

In our work, we formalize the problem in a way that can be solved to proven optimality by mixed-integer linear programming (MILP) solvers. Similarly to [8], we define a compliance measure for each characteristic within the teams. We distinguish between numerical characteristics (e.g., a real number from $[0, 1]$) and categorical ones (e.g., the nationality) and define different measures for these types. For numerical characteristics we use the largest range of values within the team, while for the categorical ones we use the number of different categories represented in the team. For each characteristic in the order of importance we solve an optimization problem that tries to adjust the measure so that within-team compliance to similarity or dissimilarity is maximized and among-team similarity is also maximized. It is easy to extend this approach with side constraints like ranges on the size of the teams or student incompatibilities of the type "two persons cannot be in the same team" or similar. Our tests conducted on instances of the problem involving up to 151 students indicate that the MILP approach exhibits notable efficiency and pratical utility. Leveraging this approach, we have successfully formed heterogenous groups and examined the efficiency of such diversified teams in enhancing students' achievement and fostering positive emotions during collaborative learning [14].

2 Problem Formulation

We want to team up a set S of students indexed by s. Each student is characterized by a set of characteristics (or factors or features) $F = \{1..m\}$ indexed by f. Some of these characteristics, $F^q \subseteq F$, are quantitative or numerical, that is, they take values in $\mathbb{R}$; others, $F^c \subseteq F$, are categorical and can be mapped to take values in $\mathbb{N}$ or $\mathbb{B}$. For example, the gender of a person can be mapped into the integer numbers 0 and 1. A categorical characteristic $f \in F^c$ takes values from a finite set of categories (or levels) $L_f = \{1..v_f\} \subset \mathbb{N}$ indexed by ℓ. Thus, a student $s \in S$ is characterized by a vector $\vec{c}(s) = [c_{s1}, \ldots, c_{sm}]$ with $c_{sf} \in \mathbb{R}$ for $f \in F^q$ and $c_{sf} \in \mathbb{N}$ for $f \in F^c$. Further, let $\pi : F \longrightarrow F$ be a permutation of the characteristics such that the permutation $\pi(1)..\pi(m)$ induces a strict total order on the characteristics (from most to least important).

We aim at combining the students in S into a set of teams $\mathcal{T} \subset 2^S$. We can denote such a team formation as a mapping $\sigma : S \longrightarrow \mathcal{T}$. Thus, $\sigma(s) = T$, if student $s \in S$ is assigned to team $T \in \mathcal{T}$. We want the team formation to be a partition of $\mathcal{T}$, that is, $T_1 \cap T_2 = \emptyset$ for any $T_1, T_2 \in \mathcal{T}$ and $\bigcup_{T \in \mathcal{T}} T = S$, and such that the size of each team T in $\mathcal{T}$ under σ is $\{\lfloor |S|/|T| \rfloor, \lceil |S|/|T| \rceil\}$, i.e., as equal as possible. Among all team formations satisfying these requirements, Σ, we want to find those that maximize within-team compliance and among-team similarity with respect to the characteristics under the order induced by π.

We formulate the preference criterion above in the following way. For a team formation σ, let $\delta_{f,p,T}$ be the absolute difference in the values of the characteristic f for any pair of students $p = (s, r)$ in T, that is, $\delta_{f,p,T} = |c_{sf} - c_{rf}|$ for all $f \in F^q$, $T \in \mathcal{T}$ and $\{p = (s, r) \mid \sigma(s) = \sigma(r) = T\}$. Then, let $\underline{\theta}_{f,T}$ and $\overline{\theta}_{f,T}$ for $f \in F^q$ be the smallest and the largest of these differences within each team T and $\underline{\theta}_f$ and $\overline{\theta}_f$ the minimum and

	Within-team heterogeneity	Within-team homogeneity
Categorical factor	$\min \overline{\eta}_f$ $\max \underline{\eta}_f$	$\min \overline{\eta}_f$ —
Numerical factor	$\min \overline{\theta}_f$ $\max \underline{\theta}_f$	$\min \overline{\theta}_f$ —

Table 1: The optimization applied for the two types of factors under the two different expression of within-team compliance (heterogeneity or homogeneity)

maximum difference throughout all teams, that is, for $f \in F^q$:

$$\underline{\theta}_f = \min_{T \in \mathcal{T}} \underline{\theta}_{f,T} = \min_{T \in \mathcal{T}, p \in T} \delta_{f,p,T}$$
$$\overline{\theta}_f = \max_{T \in \mathcal{T}} \overline{\theta}_{f,T} = \max_{T \in \mathcal{T}, p \in T} \delta_{f,p,T}$$

Similarly, for a team formation σ, let $\mu_{f,T}$ be the number different of categories of the characteristic $f \in F^c$ represented by the members of T and let $\underline{\eta}^c_f$ and $\overline{\eta}^c_f$ for $f \in F^c$ be, respectively, the smallest and largest number of categories present in any $T \in \mathcal{T}$, that is, for $f \in F^c$

$$\underline{\eta}_f = \min_{T \in \mathcal{T}} \mu_{f,T}$$
$$\overline{\eta}_f = \max_{T \in \mathcal{T}} \mu_{f,T}$$

We use $\underline{\eta}_f$ and $\underline{\theta}_f$ as measures of the within-team dissimilarity that we may want to maximize or minimize and $\overline{\theta}_f$ and $\overline{\eta}_f$ as measures of the among-team dissimilarity that we want to minimize. In Table 1, we consider the different cases. Accordingly, if we aim for within-team heterogeneity and among-team homogeneity, we aim at the following: for each categorical factor, first, we maximize the smallest number of categories in the teams, thus promoting within-team heterogeneity, and, second, we minimize the largest number of categories, thus promoting the range between minimum and maximum number of categories among the teams to be small and consequently favoring among-team homogeneity; for numerical factors, first, we maximize the smallest difference within the teams, thus promoting within-team heterogeneity, and, second, we minimize the largest value of the differences within the teams, thus aiming at the smallest range between these values and consequently promoting among-team homogeneity. If we aim at homogeneity within and among the teams we only minimize the largest number of categories and the largest overall difference.

We solve this *multi-objective optimization problem* by lexicographic optimization using the strict order π of importance on the characteristics. For the case of aiming at within-team heterogeneity, with two objectives to optimize for every characteristics each optimization problem considers the following objective:

$$\operatorname{lex}\max_{\sigma\in\Sigma}(\varphi_1(\sigma),\ldots,\varphi_{2m}(\sigma))$$

where

$$\varphi_i(\sigma)=\begin{cases}\underline{\theta}_f & \text{if } i=2\pi(f)-1 \text{ and } f\in F^q\\ -\overline{\theta}_f & \text{if } i=2\pi(f) \text{ and } f\in F^q\\ \underline{\eta}_f & \text{if } i=2\pi(f)-1 \text{ and } f\in F^c\\ -\overline{\eta}_f & \text{if } i=2\pi(f) \text{ and } f\in F^c\end{cases}\qquad \text{for } i=1..2m.$$

This means that we consider first the characteristic that is first in the order induced by π, that is, $f \in F$ such that $\pi(f) = 1$, and maximize the value $\underline{\theta}_f$ or $\underline{\eta}_f$ depending on whether f is a quantitative or a categorical factor, respectively. Once the optimal team formation with respect to this objective has been found, we set that objective as a constraint and maximize $-\overline{\theta}_f$ or $-\overline{\eta}_f$, which corresponds to minimize $\overline{\theta}_f$ or $\overline{\eta}_f$. Then, we consider the next characteristic in the order, i.e., $f \in F$ such that $\pi(f) = 2$, and repeat the process while keeping all previously optimized objectives as constraints. We proceed in this way until all characteristics are considered.

Each optimization problem can be formulated as a mixed integer linear programming (MILP) problem (see Appendix A) and solved with one of the available general-purpose MILP solvers. Artificial restrictions on the set Σ of feasible team formations, such as "student s cannot be in the same team as student r" can be easily added within the same formalism.

Consider the example of Figure 1. We have four students s_1, s_2, s_3, s_4 described by two categorical characteristics C_1 and C_2 and four numerical characteristics, C_3, C_4, C_5, C_6. The order of importance of the characteristics is $\pi = (1, 2, 3, 4, 5, 6)$. We want to group the students in two teams T_1, T_2. The table on the left shows the values of the characteristics for the four students with columns in the same order of importance of the characteristics. The signs $+/-$ indicate whether we are interested in within-group heterogeneity or homogeneity, respectively, for the corresponding characteristic.

The assignment made by the algorithm is shown in the table on the right. It corresponds to $\sigma(s_2) = \sigma(s_3) = T_1$ and $\sigma(s_1) = \sigma(s_4) = T_2$. The last two rows show the measures of compliance among the teams for each characteristic. For C_1 both teams include two categories, which is the best possible in this case. For C_2 it is not possible to have two categories in both teams because of the restriction imposed on C_1. For the following categories it seems that the situation can not improved any further because of the constraints introduced on C_1.

3 Practical Experience

We used the tool in six real-life situations on 20, 21, 79, 99, 110, 151 students with 12 or 13 characteristics of both types giving rise to a maximum of 25 objectives. We used gurobi [5] as MILP solver, which can handle lexicographic optimization automatically. On all instances except one, the full lexicographic series could be solved in less then

	C1	C2	C3	C4	C5	C6
	+	−	+	+	−	+
s_1	1	2	0.3	0.4	0.2	0.3
s_2	0	3	0.5	0.3	0.7	0.8
s_3	1	4	0.1	0.7	0.3	0.2
s_4	0	2	0.8	0.9	0.4	0.5

Team 1	C1	C2	C3	C4	C5	C6
s_2	0	3	0.5	0.3	0.7	0.8
s_3	1	4	0.1	0.7	0.3	0.2
Team 2	C1	C2	C3	C4	C5	C6
s_1	1	2	0.3	0.4	0.2	0.3
s_4	0	2	0.8	0.9	0.4	0.5
Measures	C1	C2	C3	C4	C5	C6
$\overline{\eta}_f$ or $\overline{\theta}_f$	2	2	0.5	0.5	0.4	0.6
$\underline{\eta}_f$ or $\underline{\theta}_f$	2	1	0.4	0.4	0.2	0.2

Fig. 1: A numerical example. On the left, the input data for a case with four students (on the rows) and six characteristics (on the columns), of which the first two categorical. The order of priority on the characteristics is the same as their indices and the preference for within-team similarity (+) or dissimilarity (−) is indicated in the second row of the table. On the right, the teams produced by the solution to the model.

60 seconds of time. The instance with 110 turned out harder to solve. In 1000 seconds, only the first 3 objectives were solved, the fourth proved much more computationally demanding. We decided to halt the solution process and to use the best solution found up to that point.

4 Discussion

We have developed a tool designed for team formation, which considers relevant student characteristics. Emphasizing diversity with respect to these characteristics within teams can potentially foster competence development, while maintaining similarity across teams in their treatment of student characteristics promotes fairness. We formulated these goals in a mixed integer linear programming model accommodating both numerical and categorical characteristics. We dealt with the presence of multiple characteristics by asking teachers to prioritize them a priori, thus solving a series of lexicographic optimization problems. Other approaches for managing multiple characteristics, such as weighted sum and allowing partial degradation of previous objectives, are feasible avenues to explore. While Pareto optimization presents an intriguing alternative, its implementation entails greater complexity. Our tool has undergone testing solely on real-life instances involving up to 151 students, organized into teams of 5. The results indicate that the approach is generally computationally practicable and efficient. For instances that require more computational resources, a transition from an exact to a heuristic approach is possible by allocating a limited time budget for solving each objective in the lexicographic series. This budget allocation can prioritize objectives associated with higher priority characteristics, thereby facilitating computational tractability.

We are planning to conduct scalability tests on larger artificial instances. Moreover, we would like to deepen our understanding of the solution quality and the influencing factors' impact on outcomes. Notably, as illustrated in the numerical example of Fig. 1, the situation might become blocked very early. Finally, we are actively developing a web-based application to serve as an interface for out tool, facilitating its accessiblity and usability.

Appendix A – The MILP Model

Let x_{st} for $s \in S$ and $T_t \in \mathcal{T}$ be the binary variables that denote the assignment of s to T_t under σ. Let also y_t for $T_t \in \mathcal{T}$ be auxiliary binary variables indicating whether a team T_t contains students or not. A feasible team formation $\mathcal{X}$ satisfies:

$$\sum_{T_t \in \mathcal{T}} x_{st} = 1 \qquad \forall s \in S \tag{1}$$

$$\sum_{s \in S} x_{st} \leq b_t y_t \qquad \forall T_t \in \mathcal{T} \tag{2}$$

$$\sum_{s \in S} x_{st} \geq a_t y_t \qquad \forall T_t \in \mathcal{T} \tag{3}$$

$$\sum_{s \in S} x_{s,t} \geq \sum_{s \in S} x_{s,t+1} \qquad \forall t = 1..|\mathcal{T}| - 1 \tag{4}$$

$$x_{st} \in \mathbb{B} \qquad \forall s \in S, T_t \in \mathcal{T} \tag{5}$$

$$y_t \in \mathbb{B} \qquad \forall T_t \in \mathcal{T} \tag{6}$$

Constraints (1) ensure all students are assigned to a team. Constraints (2)-(3) ensure that if a team is created it is assigned students between its lower and upper bound a_t, b_t, respectively. Constraints (4) are symmetry breaking constraints.

To compute the values $\overline{\theta}_f, \underline{\theta}_f$ we need to introduce auxiliary binary variables $z_{s_1,s_2,t}$ that are one if the two students s_1 and s_2 are in team T_t and zero otherwise. For an feasible formation $\vec{x} \in \mathcal{X}$:

$$x_{s_1,t} + x_{s_2,t} - 1 \leq z_{s_1,s_2,t} \qquad \forall s_1, s_2 \in S, \forall T_t \in \mathcal{T} \tag{7}$$

$$x_{s_1,t} \geq z_{s_1,s_2,t} \qquad \forall s_1, s_2 \in S, \forall T_t \in \mathcal{T} \tag{8}$$

$$x_{s_2,t} \geq z_{s_1,s_2,t} \qquad \forall s_1, s_2 \in S, \forall T_t \in \mathcal{T} \tag{9}$$

$$\overline{\theta}_f \geq |c_{s_1,f} - c_{s_2,f}| z_{s_1,s_2,t} \qquad \forall f \in F^q, \forall s_1, s_2 \in S, \forall T_t \in \mathcal{T} \tag{10}$$

$$\underline{\theta}_f \leq M_f(1 - z_{s_1,s_2,t}) + |c_{s_1,f} - c_{s_2,f}| z_{s_1,s_2,t} \qquad \forall f \in F^q, \forall s_1, s_2 \in S, T_t \in \mathcal{T} \tag{11}$$

$$z_{s_1,s_2,t} \in \mathbb{B} \qquad \forall s_1, s_2 \in S, \forall T_t \in \mathcal{T} \tag{12}$$

$$\overline{\theta}_f \in \mathbb{R}_0^+ \qquad \forall f \in F^q \tag{13}$$

$$\underline{\theta}_f \in \mathbb{R}_0^+ \qquad \forall f \in F^q \tag{14}$$

Constraints (7)-(9) ensure the z variable take the value described. Constraints (10)-(11) force $\overline{\theta}_f$ and $\underline{\theta}_f$ to stay above and below all realized differences, respectively. We set $M_f = \max_{s_1,s_2 \in S}\{|c_{s_1,f} - c_{s_2,f}|\}$.

To compute the values $\overline{\eta}_f, \underline{\eta}_f$ we will slightly abuse of notation and use $\eta_{tf\ell}$ and η_{tf} to indicate for characteristic $f \in F^c$ and team $T_t \in \mathcal{T}$ whether the category ℓ is represented and the number of different categories represented in the team, respectively.

$$x_{st} \leq \eta_{tf\ell} \qquad \forall s \in \{s \mid s \in S \wedge c_{sf} = \ell\}, \ell \in L_f, f \in F^c, \forall t \in \mathcal{T} \tag{15}$$

$$\eta_{tf\ell} \leq \sum_{s \in S | c_{sf} = \ell} x_{st} \qquad \forall \ell \in L_f, f \in F^c, \forall t \in Gi \tag{16}$$

$$\eta_{tf} = \sum_{\ell \in F_f} \eta_{tf\ell} \qquad \forall f \in F^c, \forall t \in \mathcal{T} \tag{17}$$

$$\overline{\eta}_f \geq \eta_{tf} \qquad \forall f \in F^c, \forall T_t \in \mathcal{T} \tag{18}$$

$$\underline{\eta}_f \leq \eta_{tf} \qquad \forall f \in F^c, \forall T_t \in \mathcal{T} \tag{19}$$

$$\eta_{tf\ell} \in \mathbb{B} \qquad \forall \ell \in L_f, \forall f \in F^c, \forall t \in \mathcal{T} \tag{20}$$

$$\eta_{tf} \in \mathbb{Z}_0^+ \qquad \forall f \in F^c, \forall t \in \mathcal{T} \tag{21}$$

$$\overline{\eta}_f \in \mathbb{Z}_0^+ \qquad \forall f \in F^c \tag{22}$$

$$\underline{\eta}_f \in \mathbb{Z}_0^+ \qquad \forall f \in F^c \tag{23}$$

Constraints (15)-(16) ensure $\eta_{tf\ell}$ is either one or zero depending on whether any student among those who have that category are assigned to the team. Constraints (17) collect the number of different categories present in the team. Constraints (18) and (19) force $\overline{\eta}_f$ and $\underline{\eta}_f$ to stay above and below the number of categories over all teams, respectively.

We can finally state the overall MILP model with the objective function defined in the main text:

$$\begin{aligned} &\operatorname{lex} \max_{\sigma \in \Sigma} \ (\varphi_1(\sigma), \ldots, \varphi_{2m}(\sigma)) \\ &\text{subject to } (1) - (6) \\ &\qquad\qquad (7) - (14) \\ &\qquad\qquad (15) - (23). \end{aligned}$$

References

1. Chan, T., Chen, C.M., Wu, Y.L., Jong, B.S., Hsia, Y.T., Lin, T.W.: Applying the genetic encoded conceptual graph to grouping learning. Expert Systems with Applications **37**(6), 4103–4118 (2010)
2. Chen, C.M., Kuo, C.H.: An optimized group formation scheme to promote collaborative problem-based learning. Computers & Education **133**, 94–115 (2019)
3. Fallucchi, F., Fatas, E., Kölle, F., Weisel, O.: Not all group members are created equal: Heterogeneous abilities in inter-group contests. Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series **14**, 1–42 (2018)
4. Graf, S., Bekele, R.: Forming heterogeneous groups for intelligent collaborative learning systems with ant colony optimization. In: International conference on intelligent tutoring systems. pp. 217–226. Springer (2006)
5. Gurobi Optimization, L.: Gurobi optimizer reference manual (2021), https://www.gurobi.com

6. Hilton, S., Phillips, F.: Instructor-assigned and student-selected groups: A view from inside. Issues in Accounting Education **25**(1), 15–33 (2010)
7. Huxham, M., Land, R.: Assigning students in group work projects. can we do better than random? Innovations in Education and Training International **37**(1), 17–22 (2000)
8. Layton, R.A., Loughry, M.L., Ohland, M.W., Ricco, G.D.: Design and validation of a web-based system for assigning members to teams using instructor-specified criteria. Advances in Engineering Education (2), 1–28 (2010)
9. Lin, Y.T., Huang, Y.M., Cheng, S.C.: An automatic group composition system for composing collaborative learning groups using enhanced particle swarm optimization. Computers & Education **55**(4), 1483–1493 (2010)
10. Liu, C.C., Tsai, C.C.: An analysis of peer interaction patterns as discoursed by on-line small group problem-solving activity. Computers & Education **50**(3), 627–639 (2008)
11. Lou, Y., Abrami, P.C., Spence, J.C., Poulsen, C., Chambers, B., d'Apollonia, S.: Within-class grouping: A meta-analysis. Review of educational research **66**(4), 423–458 (1996)
12. Manske, S., Hecking, T., Chounta, I.A., Werneburg, S., Hoppe, H.U.: Using differences to make a difference: a study on heterogeneity of learning groups. In: Lindwall, O., Haäkkinen, P., Koschman, T., Tchounikine, P., Ludvigsen, S. (eds.) Exploring the Material Conditions of Learning: The Computer Supported Collaborative Learning (CSCL) Conference 2015. vol. 1, p. 8. International Society of the Learning Sciences, Inc.[ISLS]., Gothenburg, Sweden (2015)
13. Murphy, P.K., Greene, J.A., Firetto, C.M., Li, M., Lobczowski, N.G., Duke, R.F., Wei, L., Croninger, R.M.: Exploring the influence of homogeneous versus heterogeneous grouping on students' text-based discussions and comprehension. Contemporary Educational Psychology **51**, 336–355 (2017)
14. Sun, Z., Chiarandini, M.: An exact algorithm for group formation to promote collaborative learning. In: Warschauer, M., Lynch, G. (eds.) LAK21: 11th International Learning Analytics and Knowledge Conference (LAK21), April 12–16, 2021, Irvine, CA, USA. Association for Computing Machinery, New York, NY, USA (2021)
15. Takači, D., Marić, M., Stankov, G., Djenić, A.: Efficiency of using vns algorithm for forming heterogeneous groups for cscl learning. Computers & Education **109**, 98–108 (2017)