Optimization of Playful Learning on the Unispher™ Platform by Simulation Modeling

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Abstract

Education optimization of playful learning student's groups is considered. The goal of optimization is to form groups of students who will show high performance of education using game forms of learning. The optimization is based on the student's classification according to interest and learning ability, behavioral characteristics, character traits and social characteristics, as well as on predicting their individual and group performance, considering the mutual influence and work of teachers and mentors. The students are presented by vectors of their feature's numerical assessments. The student's classification is carried out using the method of Independent Component Analysis on a data driven basis obtained by Singular Value Decomposition. The method allows to classify students' data taking into account the significance of the parameters and an uncertainty of some parameter's values through their randomization. The method allows to select students with different learning abilities and behavioral characteristics for each group in order to create conditions for the coordinated work of the group. The method allows to distribute students with special characteristics evenly into groups.

Keywords

Playful learning, optimization, independent component analysis, singular value decomposition, teaching-learning simulation model.

1. Introduction

Modern teaching methods, known as "precision education" [1-3], are based on constructing the learning process in such a way that its results are predictable and correspond to the required level of knowledge. Artificial intelligence, machine learning, and learning analytics are applying to improve both learning performance and teaching quality. For the learning outcome to be successful, it is necessary to predict not only high results, but also possible failures in order to eliminate them before they manifest themselves by concentrating the efforts of teachers and students. One of the new approaches to learning uses game forms, when students confirm their knowledge not by solving formal tasks, but by solving game problems and by creating games [4-6]. In this case, the emphasis is not on the student's individual work, but on their participation in collective work; teamwork and creative work to solve the assigned problem are practiced. The implementation of the playful learning forms is carried out by students small group, up to ten members, interacting and mutually complementing each other as a team. Every student in such group is noticeable and either actively participates in the game or drops out of the game. To get a cohesive group that works as a team, it is necessary to optimize its composition according to education targets. The optimization of the composition of student groups depends on many factors of influence. Groups of students, depending on targets of education, general education or specialized, can be formed from students with mixed or similar profiles, which are determined from information obtained by questionnaires and tests. However, students' information is not entirely accurate as it is mainly based on students' self-assessment and short conversation with experts during students testing.

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The Unispher™ platform [7] creates the information and communication basis for teachers' work with student's groups in playful form. The platform's cooperative network offers opportunities to implement new forms of learning through close interaction between teachers, students and mentors in solving problems using non-standard approaches, thus developing teamwork, creativity and ingenuity of students. The platform needs to develop optimization methods for forming groups of students in such a way as to achieve high learning results.

The authors consider it their duty to mention in this context the fundamental works and ideas of the famous scientist I.V. Kuzmin, whose centenary of birth is celebrated in 2023. In the scientific school of Professor Kuzmin, analytical and simulation models of complex systems were studied, to the class of which teaching systems certainly belong. The criteria for assessing the effectiveness, quality and optimality of complex systems proposed by Ivan Kuzmin are still relevant today [8].

2. Related Works

The main principles of groups forming for effective team working are considered in [9, 10]. For example, for general form education with playful learning organization of the education process all groups' members should be as different as possible by character and behavior. Otherwise, members close in character and behavior will either conflict or unite and thus separate the group. The optimal composition of playful student groups can be checked by simulating the learning process, taking into account the mutual influence of students, the influence of teachers and mentors on the process. By varying the numerical assessments of knowledge and behavioral characteristics, it is possible to obtain a space of assessments of the effectiveness of the learning process and values corresponding to the best estimates. According to the obtained values, adjust the composition of the groups and carry out the next simulation cycle until stable estimates of the required level are obtained.

To implement this approach, all characteristics of students should be represented by numerical values that conditionally reflect level and activity of the characteristics and their significance on the formation of the group. The classification of students in this case looks like classification of objects in the form of data vectors. The objects classes types are characterized by features which can be created using known methods of Independent Component Analysis (ICA) [11]. The distribution of students into typical classes can be done using pattern recognition methods.

Until recently, the search for optimal approaches to school and higher education was carried out using humanitarian methods of analysis and synthesis of a philosophical type. Modern methods of developing artificial intelligence (AI) initially used the same approaches, but with the development of formalizing the intellectual process in the form of mathematical models implemented by computing means, these methods have become strictly mathematical with the integration of almost all sections of mathematics and the creation of new directions. It was formed the class of teaching-learning-based optimization (TLBO) algorithms which are successfully applied to real-world problems in diverse fields [12]. This is meta-heuristic algorithm inspired by the teaching-learning process and simulates the influence of a teacher on learners. Due to the advantages of rapid convergence, absence of algorithm-specific parameters and easy implementation, TLBO has become a viral optimization algorithm for many problems [13]. This method works on the effect of influence of a teacher on learners. Like other nature-inspired algorithms, TLBO is also a population-based method and uses a population of solutions to proceed to the global solution. The population is considered as a group of learners or a class of learners.

The process of TLBO is divided into two phases: the first phase consists of the "Teacher Phase" – learning from the teacher, and the second phase consists of the "Learner Phase" – learning by the interaction between learners. The teaching process can be formulated as follows:

$$X_{new} = X_{old} + rand \cdot \left(X_{teacher} + T_F \cdot Mean\right), \tag{1}$$

where X_{new} and X_{old} represent the individual positions of a student after and before learning, $X_{teacher}$ is the position of the teacher, which is the best student, *Mean* indicates the average level in the population. T_F is a teaching factor that determines the change of the mean value, and *rand* is a random number between 0 and 1. The value of T_F can be random between 1 and 2. The expression of the learner phase can be written as follows:

$$X_{new} = \begin{cases} X_{old} + rand \cdot (X_{r1} - X_{r2})): f(X_{r1}) < f(X_{r2}) \\ X_{old} + rand \cdot (X_{r2} - X_{r1})): otherwise \end{cases}, \tag{2}$$

where X_{r1} and X_{r2} indicate the positions of two learners randomly selected from the population, $f(\cdot)$ is the fitness value. The comparison between two learners determines the learning direction. The student with a poor grade learns from the individual with a better grade. The new individual with improvements after learning will be accepted, otherwise rejected.

There are known many optimization algorithms, such as sine cosine algorithm, grasshopper optimization algorithm, meta-heuristic algorithms as follows: genetic algorithms, differential evolution algorithm, simulated annealing, arithmetic optimization algorithm etc. [14]. The method TLBO has shown its versatility in solving optimization problems in various fields, for example, the original algorithm was demonstrated using the example of mechanics [12], its other implementations are known in electronics, power supply, artificial intelligence etc. The ideology of this algorithm, based on the simulation of teaching-learning processes, is most suitable for modeling humanitarian problems, such as training of schoolchildren and students. This algorithm is interesting for the Unispher™ platform from the point of view of simulating the phase of mutual teaching of students, that is important for gaming tasks.

3. Problem Statement

The playful form of education on the Unispher™ platform is basing on small groups of students closely interacting in the process of solving educational problems by applying the acquired theoretical knowledge in the form of creating computer games. For groups to be able to solve such problems, they must be carefully selected both in terms of knowledge and behavior. In order to be covered by the learning process for all students of the same age, the groups must be approximately equal in composition. Therefore, to form groups, students must be classified according to their educational and behavioral characteristics. Groups can be formed by selecting chairs from different clusters into each group. Then the satisfaction of two conditions will be achieved: − for team work it is better to use students with the most different educational and behavioral characteristics; − all groups should be approximately equal in composition so that the teacher's efforts and time spent on teaching are approximately equal for each group.

A set of parameters for assessing and classifying students was considered in [15]. Assessment of students is carried out by experts through testing, conversation, observation. The parameters are presented in Table 1. These are previously acquired skills, interests in subjects, behavioral characteristics defined basing on Holland test [16]; Adizes types [17]; special characteristic, such as repatriate or migrant; computer knowledge; gender characteristic; ability to be leader. A student can have several assessments of skills from the set of N_{sk} items, assessments in N_{sb} subjects, one assessment of personality type in accordance with his activity − from 6 to 1, one assessment of social type − from 4 to 1, numerical designations of personal features. The priority weights of the parameters indicate the importance of distributing students with given characteristics into different groups.

An *i*-th student can be presented by the following vector of parameters:

$$st^i = \left[sk_0^i,\ldots,sk_{N_{sk}-1}^i sb_0^i,\ldots,sb_{N_{sb}-1}^i, pr^i, sc^i, gd^i, cm^i, rp^i, ld^i\right]. \tag{3}$$

An uncertainty of some parameters values st_k^i of the vector st^i due to errors in assessment can be accounted through their randomization as $st_k^i + \xi_k^i$, ξ_k^i are random values. The target functional for optimizing the distribution of students into groups based on assessments of skills and interest in subjects can be represented as

$$I = min \sum_{m=0}^{N_{gr}-1} \sum_{n>m}^{N_{gr}-1} \left(\left|sum_m^{sk} - sum_n^{sk}\right| + \left|sum_m^{sb} - sum_n^{sb}\right|\right), \tag{4}$$

where

$$sum_j^{sk} = \sum_{i \in gr_j} \sum_{k=0}^{N_{sk}-1} sk_k^i \, , sum_j^{sb} = \sum_{i \in gr_j} \sum_{k=0}^{N_{sb}-1} sb_k^i \, , \tag{5}$$

where gr_j is *j*-th group, N_{gr} – number of groups.

Table 1
Parameters of assessments student' knowledge and behavior

Characteristic	Grades diapason	Priority weight	Designation for *i*-th student
N_{sk} skills: analytical; intercular; communication; collaborative; empathy; creativity; critical thinking; global awareness; social responsibility; leadership	0...100	1	$sk_0^i,\ldots,sk_{N_{sk}-1}^i$
Interest to N_{sb} subjects:	0...5	2	$sb_0^i,\ldots,sb_{N_{sb}-1}^i$
Holland' personality types:			pr^i
realistic/doer	6	5	
artistic/creator	5	5	
social/helper	4	5	
enterprising/persuaders	3	5	
conventional/organizer	2	5	
investigative/thinkers	1	5	
Adizes' social media personal types:			sc^i
performer	4	3	
network creator	3	3	
social	2	3	
loner	1	3	
Gender feature:			gd^i
boy	+1	5	
girl	-1	5	
Computer	0/1	5	cm^i
Repatriate/migrant	0/1	10	rp^i
Leader	0/1	10	ld^i

The functional (4) means that variations of sum (5) between groups should be minimal. It is desirable that the variations of sum like (5) for each subject also be minimal. Functional (4) does not contain an argument that will allow the Lagrangian formalism to be used to find the minimum, so it can be optimized using heuristic methods such as TLBO. The following conditions of students' distribution with features in the vector (3) limit the range of minima of the functional (4):

$$\sum_{i \in gr_j} pr^i > 0 \, ; \sum_{i \in gr_j} sc^i > 0 \, ; \sum_{i \in gr_j} gd^i \approx 0 \, ; \sum_{i \in gr_j} rp^i > 0 \, ; \sum_{i \in gr_j} ld^i > 0 \, . \tag{6}$$

The main target of the student's distribution and playful learning group formation is to achieve high performance in education, that can be formalized as

$$J = max \left\{ \sum_{j=0}^{N_{gr}-1} sum_j^{sb} \right\} . \tag{7}$$

As it follows from defined functionals (4), (7) and conditions (6), the optimization includes three steps: 1) achieving balance in the distribution of students into groups; 2) rotation of groups composition in order to best suit the conditions (6); 3) simulation of the learning process taking into account the influence of teachers, mentors and taking into account the mutual influence of students in the groups [18]. As a result, the value of functional (7) is analyzed. This way can be repeated for other group compositions until the best composition in the terms of maximum of functional (7) is found. The problem is to find effective approach to solve this optimization task.

4. Students Classification and Distribution by Groups

The approaches to student's classification and groups compilation basing on histograms of characteristics parameters and decision making algorithms, by Python Scikit package were considered in [18]. Also, the approach based on the Independent Component Analysis (ICA) in data driven basis given with using the Singular Value Decomposition (SVD) of the matrix $\mathbf{X} = \lfloor st^i \rfloor_{i=0...N_{st}-1}$ compiled by rows of students' data (3) of size M, N_{st} is number of students [19] was proposed. The SVD of the matrix of size $N_{st} \times M$ is the following.

$$\mathbf{X} = \mathbf{U} \cdot diag[s_0 ... s_{M-1} 0_M ... 0_{N_{st}-1}] \cdot \mathbf{V}^T , \tag{8}$$

where $\mathbf{U}$ is the matrix of size $N_{st} \times N_{st}$ of unitary orthogonal columns, $\mathbf{V}$ – the same matrix of size $M \times M$, $diag[\;]$ – the diagonal matrix of size $N_{st} \times M$ with vector $\mathbf{s}$ of singular values: $s_0 > s_1 > ... > s_{M-1}$, T – is the transposition. The number of non-zero singular values is equal to the rank of the matrix, it indicates the number of non-collinear rows or columns in the matrix $\mathbf{X}$. The priorities of students parameters are given by the vector of weights $\mathbf{w} = [w_i]_{i=0...M-1}$ which example is presented in Table 1. The weighted data matrix can be presented as

$$\mathbf{X}_w = \mathbf{X} \cdot diag[\mathbf{w}] . \tag{9}$$

The substitution of the SVD in (9) yields

$$\mathbf{X}_w = \mathbf{U} \cdot diag[s] \cdot (diag[\mathbf{w}] \cdot \mathbf{V})^T . \tag{10}$$

Equation (10) shows that data driven basis $\mathbf{V}$ does not depend from weighting of data.

If the number of student in the group $M_{st} < M$ then can be defined M_{st} mutually independent clusters $\mathbf{C} = [C_i]_{i=0...M_{st}-1}$ of students. The M_{st} main orthogonal vectors $\mathbf{v}_j$ of the matrix $\mathbf{V}$ can serve as features of the clusters. Each group can be formed by selecting one representative from each cluster. The selected students on such condition will be as diverse as possible. The clusters $\mathbf{C} = [C_i]_{i=0...M_{st}-1}$ of students' parameters vectors identifiers (ID) can be defined by sequentially selection of $int(N_{st} / M_{st})$ maximums with account priorities weights:

$$i_{\max} = \underset{i: i \notin \mathbf{C}}{argmax} \sum_{k=0}^{M-1} st_k^i \cdot w_k \cdot v_{k,j} ; \;\; i_{\max} \Rightarrow C_j \tag{11}$$

for each cluster C_j, j sequentially changing as $0,..., M_{st} - 1$. The maximum which ID was not fixed in clusters set $\mathbf{C}$ is appended to cluster C_j.

The example of using the classification (11) for distribution of 153 students into 17 game groups of 9 members is shown in Fig. 1. It was used the weight vector in Table 1. The color map of the given groups shows identifiers of groups and students in the outer circle, then colored markers of leaders, repatriates, then circles of personification and socialization markers, gender markers, distribution of interest assessments in subjects, levels of skills. As it follows from the map, the resulting distribution corresponds to the assigned target of groups compilation with as many different behavioral types as possible with different interests and skills. It is also clear that the composition of the groups is approximately equal.

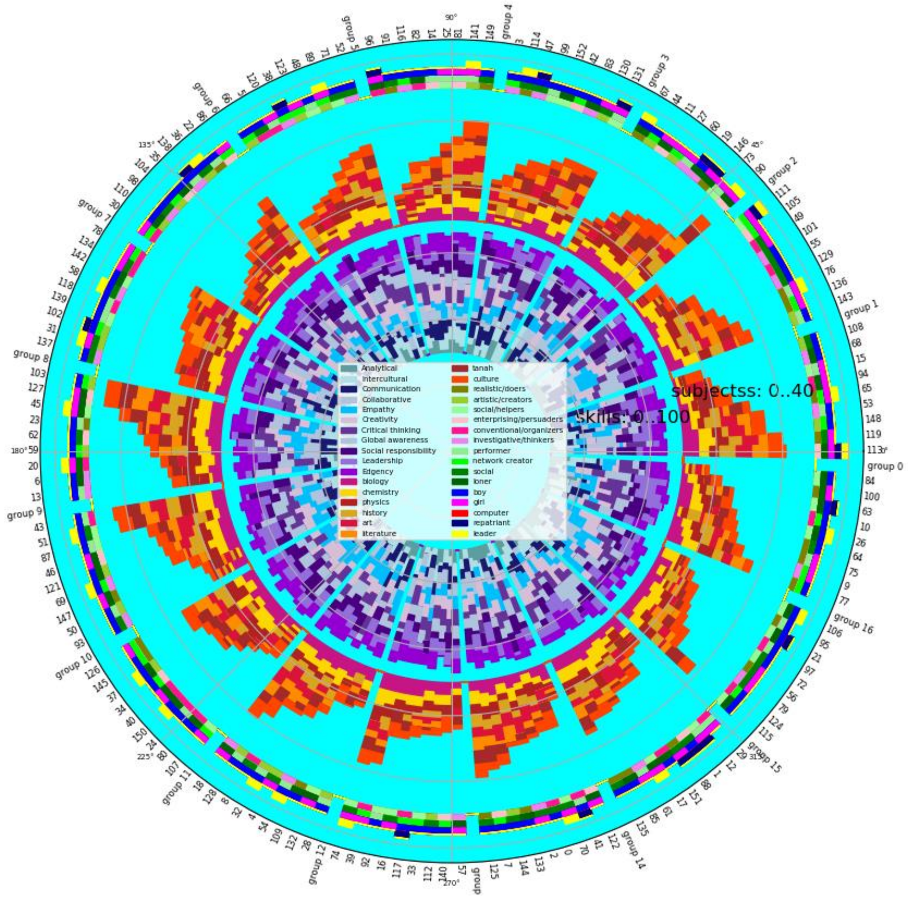

Figure 1: Color map of students' classification and distribution into groups by ICA method.

5. Simulation of Teaching-Learning Group Grades

The simulation of students group grades was considered in [18]. The model to simulate grades is basing on assessments of students interests to subjects, their mutual influence accounting their behavioral types, an impact of teachers and mentors. The model allows to investigate optimality of the education process in accordance with TLBO problem in the form (1) and (2).

The teaching process (1) can be assessed by student' own grades obtained with the help of teacher and mentor.

$$h_k^i(t) = round\left(h_k^i(t-1) + \theta \cdot \left(1 + \frac{maxgr - h_k^i(t)}{maxgr}\right) \cdot (r(t) + \mu_\theta) + \right.$$

$$\left. + \vartheta \cdot \left(1 + \frac{maxgr - h_k^i(t-1)}{maxgr}\right) \cdot (r(t) + \mu_\vartheta) \right); \tag{12}$$

$$\left| h_k^i(t) - h_k^i(t) \right| \le maxgr/2; \;\; h_k^i(0) = sb_k^i;$$

$$if \;\; h_k^i(t) < 0 \;\; h_k^i(t) = 0; \;\; if \;\; h_k^i(t) > maxgr \;\; h_k^i(t) = maxgr,$$

where $h_{k,t}^i$ are the grades of *i*-th student on *k*-th subject for time sample $t = 0,1,\ldots,N-1$, instead of $h_k^i(t)$ an updated value can be used in the form

$$h_k^i(t) = sb_k^i + r(t) \cdot (\alpha - sb_k^i) \tag{13}$$

with coefficient α that determines a spread of values, the impact of a teacher and a mentor is regulated by coefficients θ, ϑ, the impact depends on the difference between a maximal grade – $maxgr$, and the previous grade, the success of the impact is randomized using normal random variables

$r(t) = rand$ with biased means μ_θ and μ_ϑ so that the impact is predominantly positive. The model (12) assumes that the teacher and the mentor pay more attention to students with low grades.

The learning process (2) is a mutual exchange of knowledge between students in the process of solving problems in a group; it is also the realization of the abilities of each student, the realization of his knowledge. Unlike the general scheme (2), in our process we should consider the activity of each group member, their influence on other members and on the process of solving problems in a game form. In [18] heuristic matrices of mutual influence of students depending on behavioral characteristics are presented. The matrix of the mutual influence for *k*-th subject can be defined

$$A^k(t) = \left[r(t)\cdot\beta\cdot\frac{\left|h_k^i(t)-h_k^j(t)\right|}{maxgr} + \gamma\cdot r(t)\cdot T\left(pr^i, pr^j\right) + r(t)\cdot\chi\cdot T\left(sc^i, sc^j\right) \right]_{i,j\in G}, \quad (14)$$

where G is the group size, β, γ, χ are the parameters for regulation of elements' constituents of the matrix (14), the first one is associated with subject interests of students, the greatest mutual influence have strongest and weakest students, this influence is normalized to maximal grade, the next ones are associated with the behavioral characteristics of students and are defined by the tables $T()$ in [18]. Considering matrix (14), the dynamics of group' grades can be represented as a correction of the individual grades (12).

$$\begin{aligned} &g_k^i(t) = round\left(h_k^i(t) + (1-\eta\cdot ld^i)\cdot \sum_{j\in G,\, j\neq i} a_{i,j}^k(t)\cdot(1+\eta\cdot ld^j)\cdot h_k^j(t) \right); \\ &\left|g_k^i(t)-g_k^i(t-1)\right| \le maxgr/2; \qquad (15) \\ &if\ \ g_k^i(t)<0\ \ g_k^i(t)=0;\ \ if\ \ g_k^i(t)>maxgr\ \ g_k^i(t)=maxgr, \end{aligned}$$

where $g_k^i(t)$ are group grades of the *i*-th student on *k*-th subject, $a_{i,j}^k(t)$ are the elements of the matrix $A^k(t)$ (14), if *j*-th student is leader then in accordance with Table 1 $ld^j = 1$ otherwise $ld^j = 0$, η is the parameter of leadership level, $0 \le \eta < 1$. It was accounted in (14) by $(1+\eta\cdot ld^i)$ that the group' leader has a prevailing influence on others group' members, the $(1-\eta\cdot ld^i)$ means that group' members have less influence on the leader.

6. The Problem of Group Teaching-Learning Process Optimization

The simulation model (12) - (15) is regulated by the vector of parameters

$$\Lambda = \left\lfloor \alpha, \beta, \gamma, \chi, \theta, \mu_\theta, \vartheta, \mu_\vartheta, \eta \right\rfloor. \quad (16)$$

The vector regulates: grades' distribution around of assessment of interest to subject - α; mutual influence of students defined by difference in grades - β, by difference in personality types - γ, by types difference in social media - χ; teacher' impact - θ, μ_θ; mentor' impact - ϑ, μ_ϑ; leader' influence - η. The goal of the optimization is to obtain group grade dynamics with positive trend on condition of parameters (16) - $\tau(\Lambda)$, for each *k*-th subject:

$$\sum_{j\in G} g_k^j(t\mid\Lambda) \propto \sum_{j\in G} sb_k^j + \tau(\Lambda)\cdot t:\ \ \tau > 0\,. \quad (17)$$

The trend can be estimated as the following

$$\tau = \frac{1}{NN_{gr}} \sum_{t=1}^{N-1} \sum_{j=0}^{N_{gr}-1} \left(g_k^j(t) - g_k^j(t-1) \right),$$

where N_{gr} the number of students in the group. The composition of the groups also plays an important role. We will assume that the initial composition is optimized according to (11) and in the future the group members' rotation will be required only for those students who drop out from group work.

The problem of education process optimization in the form (17) does not have explicit dependence of the model parameters and the condition $\max\{\tau(\Lambda)\}$, so this problem can be solved similarly to problems solved using artificial intelligence. The algorithm for solving it is similar to algorithm of finding maximum of given condition in TLBO. The algorithm includes the following steps:

1. Define an initial vector Λ_0 (16) and simulate an ensemble of grades (15) realizations to estimate average $\tau(\Lambda_0)$ as coefficient of one-parameter regression.
2. Find variation parameter, for example θ, and change it as $\theta + \delta\theta \le \theta_{max}$ within acceptable limits to define the new vector Λ.
3. Simulate an ensemble of grades (15) realizations with new vector Λ and evaluate $\tau(\Lambda)$.
4. If $\tau(\Lambda_0) < \tau(\Lambda)$ and $\tau(\Lambda) < \tau_{min}$ (an appropriate trend): the variation of the parameter on the previous step gave a positive trend increase and it does not exceed the limit value, then this parameter can be changed in the same direction of variation. If it reached the limit value, then another parameter is varied. If $\tau(\Lambda_0) \ge \tau(\Lambda)$ then changed parameter should be recovered and another parameter should be chosen to vary. Then steps 2-4 are repeated with the changing $\Lambda \to \Lambda_0$.
5. If τ_{min} is reached then test the solution on stability, variate students' parameters as an error in their assessments. If τ remain positive along variations then the optimization is completed, otherwise it should be continued with other value of τ_{min}. If τ_{min} is not reached by the parameters changing then it should be analyzed the influence of parameters (16) and the associated with them weight values of the student classification parameters in Table 1 should be changed. The students clusters should be rearranged with using (11) and the new composition of the groups should be made.

The result of simulation with optimization is assessment of minimal teacher' and mentor' efforts to reach a positive result of education. As well, an assessment of group leader and identification of process' participants' weak positions which demand additional efforts to their overcome.

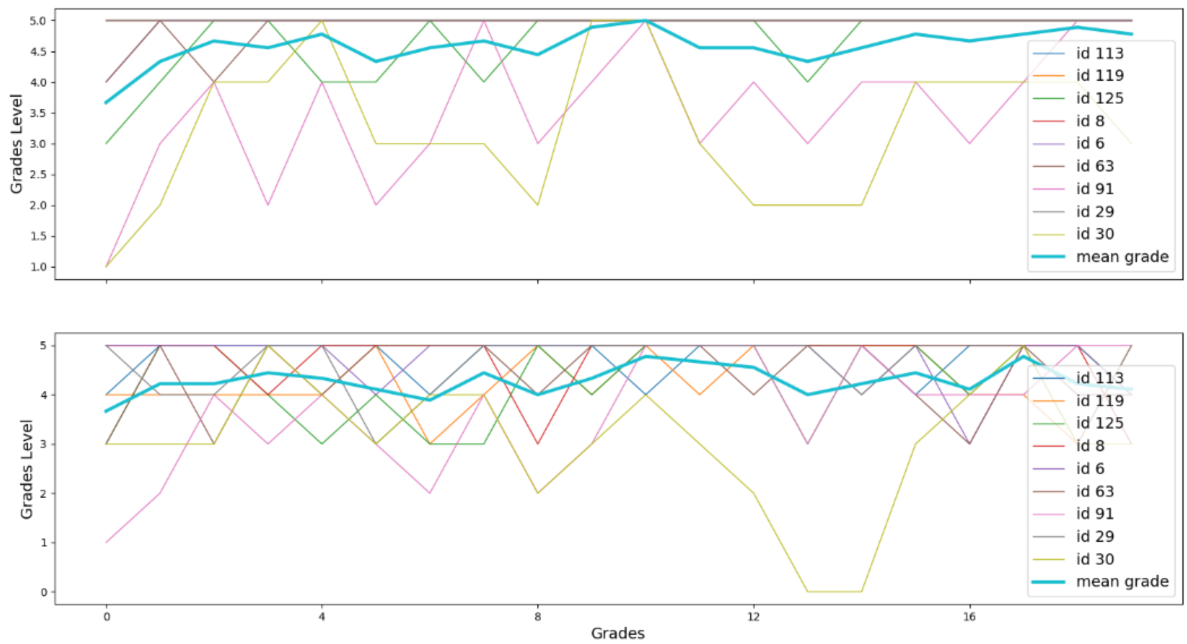

Figure 2: Simulation of optimized students' own grades (12) (high) and group grades (15) (low).

The example of grades simulation with optimization is shown in Fig. 2. The figure shows the dynamics of twenty grades of students of one of the groups; students' identifiers and their color spectrum are given in the legend of the figure. The mean grades are represented by a thick blue line. The trend of students' own mean grade $\tau = 1.19$, group mean grade $\tau = 1.14$. The initial trend was negative in both cases, it was increased by increasing the coefficients of teacher and mentor impact. The vector of model' parameters is the next: $\Lambda = [0.55,\ 0.25,\ 0.25,\ 0.3,\ 2.0,\ 0.5,\ 2.0,\ 0.5,\ 0.3]$. As can be seen from Fig. 2, group learning brought students' grades closer together, with the exception of one student with the lowest level of interest in the subject, his grades are unstable. This was achieved through strengthening the influence of teachers and mentors. According to the model (12), teachers pay more attention to weak students, which raises their grades up to the level of average students. This impact outweighed the negative impact of weak students on group grades through the elements of the matrix (14).

7. Conclusion

The methodology of creating group of people to work as a team is essential in recruiting in many areas of manufacturing. The gaming form of learning by creating games with the distribution of roles in the group simulates teamwork and can be used for both teaching and training.

This paper considers the problem of optimizing the composition of groups by weighted setting parameters depending on their priority. Clustering of students is proposed based on given parameters and their weights by the method ICA, which is implemented using SVD. By changing the weights of the parameters, clustering can be carried out both for general education and for specialized training. In the case of general education under consideration, the formation of groups is carried out by mixing students from different clusters. This makes it possible to obtain groups approximately equal in learning ability, behavioral characteristics, gender and in social activity.

Also, the problem of finding optimal interaction between students and teachers in such a way that the learning process is progressive is considered. By varying the parameters of the model and its simulation for each group of students, a multidimensional surface can be obtained that displays the dependence of the trend of learning assessments, the local maxima of which can be selected as options for the required learning parameters that set the requirements for teachers, mentors and group leaders. School management can take this into account when distributing teachers and teaching loads among student groups. The simulation results indicate problematic issues that can be eliminated if attention is paid to them in time.

The grades obtained through the simulation can be compared with the actual assessments of the students and thus evaluate the expected learning outcomes with those actually achieved. This will allow objectively to assess the work of teachers and the teamwork of students.

In order for the learning process to be completed successfully, it is necessary to select group members in such a way that their interaction is effective and predictable. This problem is very complex and can be solved by simulation with multi-criteria optimization. Significant ideas for the development of this scientific direction were laid in the last quarter of the 20th century by the rector of VNTU, Professor I.V. Kuzmin, to whose centenary of birth this work is dedicated.

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