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Class Schedule Assignment Based on Students Learning Rhythms Using A Genetic Algorithm

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Abstract

The objective of this proposal is to implement a school day agenda focused on the learning rhythms of students of elementary and secondary schools using a genetic algorithm. The methodology of this proposal takes into account legal requirements and constraints on the assignment of teachers and classrooms in public educational institutions in Colombia. In addition, this proposal provides a set of constraints focused on cognitive rhythms and subjects are scheduled at the most convenient times according to the area of knowledge. The genetic algorithm evolves through a process of mutation and selection and builds a total solution based on the best solutions for each group. Sixteen groups in a school are tested and the results of class schedule assignments

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are presented. The quality of the solution obtained through the established approach is validated by comparing the results to the solutions obtained using another algorithm.

Key words: learning rhythms, genetic algorithm, class schedule, optimization, logistic.

Highlights

• The computational model presented is a genetic algorithm. • The methodology developed achieves an improvement of 12% (based on the rhythms as cognitive) than traditional algorithms generate schedules. • The algorithm shows high stability in the found solutions, ensuring an effieciency over 92% in the result obtained in each cycles.

Asignación de horarios de clase basado en los ritmos de aprendizaje de los estudiantes usando un algoritmo genético

Resumen

El objetivo de esta propuesta es implementar un horario escolar que tenga en cuenta los ritmos de aprendizaje en los estudiantes de educación primaria y secundaria, utilizando un algoritmo genético. La metodología considera los requerimientos legales y las restricciones necesarias para la asignación de maestros y aulas en instituciones educativas públicas de Colombia. Adicionalmente, se establecen un conjunto de restricciones relacionadas con el enfoque en los ritmos cognitivos, determinando las horas de la jornada en las que es más conveniente la ubicación de ciertas materias de acuerdo al área del conocimiento al que pertenecen. El algoritmo genético evoluciona mediante un proceso de mutación y selección, a través del cual se construye una solución completa a partir de la búsqueda de las mejores soluciones por grupo. Se presentan los resultados de las pruebas realizadas para la asignación de una institución con 16 grupos. La calidad de las soluciones obtenidas de acuerdo al enfoque establecido es validada mediante la comparación de los resultados obtenidos con las soluciones de otro algoritmo.

Palabras clave: ritmos de aprendizaje, algoritmos genéticos, horario de clase, optimización, logística.

1 Introduction

School day is the time that primary and secondary schools establish for teaching and learning activities. The assignment of class schedules must meet the standards of current legal requirements, the institutional educational project and also the curriculum of the school. In general, the planning of the school day is based on the availability of teachers and classrooms and takes into account some special conditions of each school and the overlapping of class assignments. However, the assigning of class schedules must also consider the academic performance of students. Many schools fail to see the importance of academic performance when assigning class schedules, thus the learning rhythms of the students are not taken into account. The mental activity of human beings is subject to cycles of greater or lesser degree of accuracy when performing tasks, which vary in frequency. So, students do not always have the cognitive capacity to assimilate certain knowledge or to carry out certain learning activity at any given time of the day. There has been a lot of research done on the learning rhythms of students, also known as circadian rhythms (periods between 20 and 28 hours), which facilitate the analysis of performance according to factors such as characteristics of the task (complexity, motor component), individual differences (age, sex, chronotype, cognitive style, level of motivation) and socio-cultural factors (urban, rural) [1].

The school day (morning or afternoon) is a continuous program divided into predetermined time periods for teaching and learning activities of a number of subjects. These subjects are associated with a specific grade level, and are taken by a group of students not by choice, as university courses, but as mandatory courses. Class arrangements take into consideration the conditions of the school facilities and classrooms are permanently assigned to the same group, systematically favoring the rotation of teachers among classrooms. Multi-purpose classrooms or classrooms for special purposes can also be considered when assigning class schedules as these may turn into permanent classrooms for any of the groups at any given time. Moreover, the assigning of schedules must ensure that a teacher is not placed in two different groups at the same time, or that the weekly schedule assignment for each teacher does not exceed a preset number of hours of supervised work.

In a high proportion of institutions, the class schedule is manually made, which additionally of taking either days or weeks of work, does not allow to set certain types of restrictions that optimize the use of both resources human and infrastructure, as well as give errors for subjects overlaps and the teachers' assignation (Flores Pichardo, 2011). However, at the investigative level this proposal is not beyond the scope of previous work in which a wide variety of techniques have been applied to solve scheduling problem [2] based on models such as integer programming [3],[4] linear programming [5], Backtraking [6],[7] multi objectives scheduling [8] evolutionary algorithms [9],[10],[11] metaheuristics [12], mathematical models based on polynomial reduction [13], taboo search [14] and expert systems [15] among others [16],[17],[18].

Nevertheless, this research establishes a class schedule structure that embraces not only the constraints of infrastructure and general capacity of the school, but also includes an approach to a pedagogical practice that considers the times of the day that are more conducive to the learning of certain subjects. The questions of when to teach, or what is the best time to carry out certain academic activities become an important focal point. There are different approaches specifically addressing three types of lines: the first refers to the implementation of a double shift school day or a split shift [19]; the second refers to the duration of the school day [20]; and the third refers to the best time of the day to carry out specific learning actions [1].

The approach of this proposal deals with the most appropriate time of the day for teaching and the considerations made by Hederich [1] were adapted and adjusted to the general parameters of public educational institutions in Colombia, where the school day is continuous and lasts six hours. Three instances of time in which attention and cognitive activity are more conducive to certain types of subjects were determined. The chosen schedule, which attempts to concentrate the most difficult subjects in the middle of the day is presented in the methodology section and is identified as the time window in which students have a greater attention span and a better cognitive disposition.

The computational model presented in this paper is a genetic algorithm, which although it has been used repeatedly to solve the traditional approach to the problem [21],[22],[23], has properties that allow to cover comprehensively the multiple needs presented, including the set of constraints associated with cognitive rhythms, which increase the complexity of the problem.

In summary, the assigning of class schedules will be focused on the learning rhythms of the students. This is done through the use of a genetic algorithm which seeks to solve and optimize a class schedule in which the location of subjects will depend on constraints of the activities planned, so that these match the time of the day when the cognitive ability of the students is more suitable. These optimization criteria are not compatible with optimization criteria commonly used in school planning, because the above are not always focused on the student.

2 Methodology

Figure 1 generally describes the methodology developed for the solution of the problem in this research:

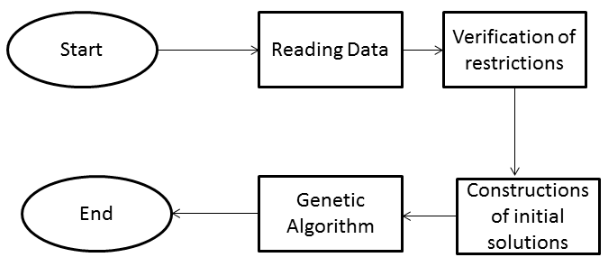

Figure 1: Scheme of the algorithm. Adapted and translate [24].

Basic information such name of the subjects, identification codes for each subject (regardless of group), names of the teachers teaching each subject, identification codes for each teacher, current weekly hours per subject, name of the group taking each subject, area identification codes for the area of each subject (this code is an identifier of the area of knowledge in which a subject is located, for example, subjects like math, calculus, and geometry belong to the area of sciences), and identification numbers for the classrooms where each subject is to be taught, was taken into account to structure class schedules

Since this is a program focused on the characteristics of educational public institutions, the information provided must adhere to two basic conditions, which are previously verified before giving way to finding a solution [25]: a) Each group must take 30 hours of class a week. b) A total of 22 hours of class will be assigned to a teacher each week.

Once the data is validated, initial solutions are structured and these correspond to four hipermatrices[1] (final solutions) in which the information of each group concerning subjects, teachers, codes of knowledge area, and code of classrooms are randomly added. Figure 2 shows the arrangement in which such hipermatrices are constructed.

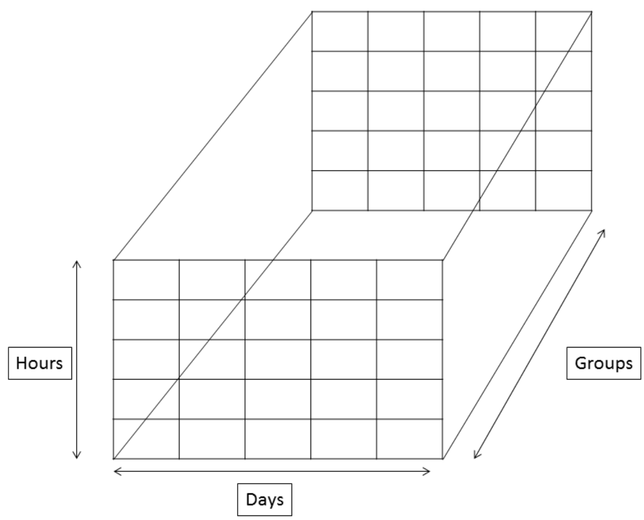

Figure 2: Hypermatrix Solutions. Adapted and translate [24].

The initial solutions provide the input for the implementation of the genetic algorithm, which is described in Figure 3:

[1] Three-dimensional matrix

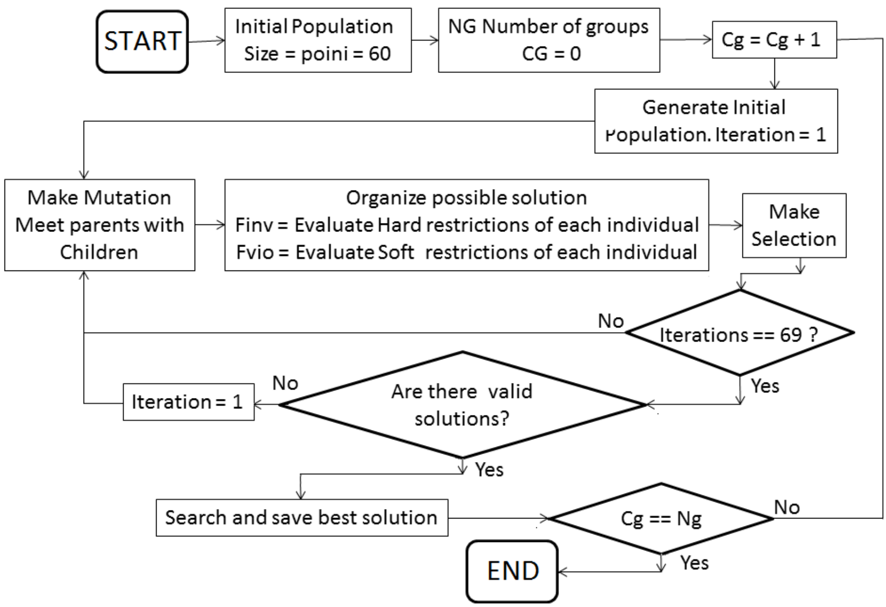

Figure 3: Implementation scheme of the genetic algorithm.

The first step of the algorithm is to determine the initial population size (vector named Parents - chromosome). The dimension must be between L and $2 * L$, where L is the size of the input vector, which in this case is 30 positions corresponding to each class hour to be scheduled in each group. The next step is to specify the number of groups (NG) and the counter begins (cg) shifting the group on which the algorithm is applied. This mechanism allows the best solutions for each group and not just an overall optimal solution.

The initial solution is taken in each group. Other solutions are randomly generated using the elements of this initial solution, until the size determined in the initial population is reached. The maximum size of the initial population, that is $2 * L$, was considered in order to cover a wider solution space and to allow the attaining of a more optimal solution. The counting of the iterations was then reset to zero, which represents the number of generations to be found before evaluating whether or not there are any valid solutions. For this case, a parameter of 70 iterations was chosen, which was found experimentally by selecting the average value at which the algorithm guarantees at least one valid solution for the group.

The next step is to apply mutation (3%) to each individual in the initial population in order to find new individuals (Children). Two random positions within the vector (named Parents) of each individual are determined, and the sub-vector contained within those two positions is inversed. This particular genetic algorithm does not perform crossover as the genetic content of the individuals would be altered by using this coding method, resulting in invalid solutions. In some cases, a solution might never be found.

Once the parents and children are obtained, they are gathered in one community to further evaluate the hard and soft constraints and thus verify the validity and level of optimization of the solutions. Hard constraints take into consideration general conditions of the school scheduling problem and are as follows: a) No more than 2 hours on the same subject matter should be taught in one single day. b) A block should be scheduled when two hours on the same subject are to be taught in one day. c) A teacher cannot teach 2 subjects at the same time of day. d) Two classes cannot be scheduled at the same time in the same classroom.

These constraints are evaluated in the Hypermatrix of subjects, teachers and classrooms. The solution is invalidated when there is not full compliance with these constraints. Soft constraints refer to learning rhythms and its evaluation determines the quality of the solutions, according to the location of each subject during the time of day. Taking into account the information in Table 1:

Table 1: Description of soft constraints.

Constraints	Description
R_1	It covers subjects in which students are more willing to receive their content in the first and second hour of the school day. Subjects from the areas of natural sciences and social sciences are examined here.
R_2	It covers the subjects in which students are more willing to receive their content in the third and fourth hour of the school day. Subjects from the areas of science and languages are examined here.
R_3	It covers subjects in which students are more willing to receive their content in the fifth and sixth hour of the day. Subjects from the areas of sports, technology and crafts are examined here.

These constraints are evaluated in the hypermatrix of knowledge area codes. Using the evaluation function in Equation (1):

$$\text{Function } (\textit{fitness}) = \min\left(\sum_{i=1}^{NG}\sum_{j=1}^{5}\sum_{k=1}^{6} F_{Soft-Const}\left(codes\left(i,j,k\right)\right)\right) \quad (1)$$

Where:

i = variable to traverse the total number of groups to be programmed;

j = variable to traverse the days of the week;

k = variable to traverse the hours of the day.

$F_{Soft-Const}(codes(i,j,k)$ = Evaluation function of soft constraints in the hypermatrix of the knowledge area codes. Depending on the knowledge area code, only one constraint per iteration is evaluated.

Table 2 shows the penalized low grade values held by each constraint according to the location of each subject at a certain time of the school day. A greater penalty is given to the subject located the farthest from its ideal position (Table 1).

Table 2: Soft constraint penalized values. Adapted and translate [24].

Time of the school day	Penalized value Constraint 1	Penalized value Constraint 2	Penalized value Constraint 3
Hour 1	0	$2 * Factor$	$1 * Factor$
Hour 2	0	$1 * Factor$	$1 * Factor$
Hour 3	$1 * Factor$	0	$2 * Factor$
Hour 4	$1 * Factor$	0	$2 * Factor$
Hour 5	$2 * Factor$	$1 * Factor$	0
Hour 6	$2 * Factor$	$2 * Factor$	0

Where, Factor = 3.

The selection of new individuals takes place once the constraints described above are evaluated and the results are stored in their respective variables. Therefore, a vector that describes pairs with individuals of the community is generated in order to confront each other in a duel in which one of them is rejected and the other is selected for the next generation, thus: a) The solutions to be confronted are taken according to the vector of pairs. b) The values of verification of the soft constraints are compared and the lowest (preferably zero) is chosen. If both are of the same value, the next step is taken. c) The values of verification of the soft constraints are compared in each solution and the lowest is chosen. If both solutions are of the same value, one is randomly chosen, since they are considered genetically equal. The above process is repeated until 70 iterations are completed, and then it is corroborated whether valid solutions are found in the last selected population. That is to say, the verification vector of the hard constraints has at least one zero (0), if not the count is reset and another 70 iterations are completed. If the result is positive, the best result is selected and the process continues for the next group. Upon completion of all groups, the final chosen solution is shown.

3 Experimentation

The previous methodology was tested for the assigning of class schedules in a high school[2] in the city of Manizales. This particular school has 16 groups between sixth and eleventh grade. There are three groups per level in sixth, seventh, eighth and ninth grade, and two groups per level in tenth and eleventh grades. The algorithm was implemented during 4 cycles, and 10 solutions to the problem were found in each cycle. The Initial data were registered in an excel file, using the information of Table 3:

Table 3: Problem.

Subjects	**Teacher**	**Hours**	**Grade**	**Classroom**	**AreaCode**
Math	1	5	6-2	3	1
Social Sciences	2	3	6-2	5	4
Spanish	3	5	6-2	8	2
:	:	:	:	:	:
:	:	:	:	:	:
:	:	:	:	:	:
Ethics and values	4	1	11-2	9	5

4 Results and Discussions

The Table 4 presents the results of the evaluation function of the 10 total solutions of the problem in each of the four cycles. The best solution found during the 40 iterations corresponds to a value of 1068 in its evaluation function.

[2]Educational Institution San Jorge School.

Table 4: Results of the evaluation function in 4 Cycle.

	Iterations									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Cycle 1	1131	1137	1155	1107	1098	1167	1131	1128	1110	1086
Cycle 2	1113	1068	1125	1134	1143	1128	1113	1128	1137	1164
Cycle 3	1107	1143	1167	1131	1137	1113	1128	1068	1134	1107
Cycle 4	1131	1068	1125	1131	1143	1113	1128	1110	1164	1131

The solutions' values were compared in each cycle using ANOVA analysis, in order to establish whether there are significant differences among them (Table 5).

Table 5: Analysis of variance-own methodology.

	Sum of squares	**gl**	**Mean square**	**F**	**Sig.**
Inter-groups	18.900	3	6.300	.010	.999
Intra-groups	23265.000	36	646.250		
Total	23283.900	39			

The variance analysis in Table 5 shows that the significance value is higher than 5%($p \geq 0.05$), and consequently it can be said that the results obtained are statistically equal, which proves the stability of the algorithm.

Subsequently, another variance analysis was performed to determine if both methods have significant differences (Table 7) using the solutions generated in cycles 1 to 3 of Table 3, and also 10 values of the evaluation function of the solutions found by the commercial software (CS) [26] used for the generation of class schedules (Table 6). Another variance analysis was performed (Table 6) to determine if there were significant differences between the optimization levels for the methodology proposed and the CS results (Table 7).

Table 6: Evaluation function results in CS solutions.

	Iterations									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
SS	1314	1257	1284	1323	1218	1350	1314	1305	1284	1290

Table 7: Variance analysis-own methodology Vs. CS.

	Sum of squares (Sq)	**gl**	**Mean square**	**F**	**Sig.**
Inter-groups	214987.275	3	71662.425	86.146	.000
Intra-groups	29947.500	36	831.875		
Total	244934.775	39			

Table 8: Post hoc analysis. Tukey test.

(I) Sample	**(J) Sample**	**Mean difference(I-J)**	**Standard Error**	**Sig.**
	3	1.5	12, 899	0.999
1	Sq	−168.900	12.899	0.000
	1	0.3	12, 899	1
2	3	1.8	12.899	0.999
	Sq	−168.600	12.899	0.000
	1	−1.5	12, 899	0.999
3	2	−1.8	12.899	0.999
	Sq	−170.400	12.899	0.000
	1	168.900	12, 899	0.000
SS	2	168.600	12.899	0.000
	3	170.400	12.899	0.000

Table 7 shows that the significance of the test is less than 5%($p \leq 0.05$), therefore there are statistical differences between the means of the results obtained. The Tukey test was applied to confirm that the difference are between the samples of the own model and the CS (Table 8). It was found in the contrast tests that the results obtained of the evaluation function in the execution cycles always showed significant differences with the CS, being always less for the results of the proposed algorithm.

Finally in this point two real solutions are illustrated. The first solution represents this methodology (Table 9 *left*) *Fitness* 1086 and the second solution represents the CS methodology (Table 9 *right*) *Fitness* 1238.

Table 9: This methodology. *Fitness* 1086 (*left*) and CS. *Fitness* 1238 (*right*).

		Group 1					**Group 1**		
biology	arts	social	biology	biology	biology	social	tic	biology	religión
math	biology	physical	physical	english	biology	etichs	tic	spanish	english
social	tic	math	math	math	spanish	spanish	social	math	social
english	math	tic	spanish	social	physical	math	math	math	math
spanish	english	english	spanish	spanish	english	english	spanish	english	arts
etichs	spanish	etichs	tic	religión	etichs	biology	spanish	tic	physical
		Group 2					**Group 2**		
etichs	tic	religión	math	english	tic	math	math	math	biology
arts	social	math	spanish	biology	spanish	arts	spanish	social	spanish
math	english	spanish	spanish	biology	etichs	english	physical	english	spanish
spanish	physical	english	etichs	math	math	biology	social	english	physical
english	spanish	tic	physical	math	religión	social	tic	biology	tic
tic	biology	biology	social	social	english	spanish	biology	etichs	math
		Group 3					**Group 3**		
physical	spanish	biology	social	tic	math	english	spanish	spanish	tic
tic	spanish	biology	social	etichs	english	english	biology	physical	math
english	social	religión	english	english	tic	physical	math	biology	math
biology	etichs	math	english	spanish	biology	spanish	etichs	biology	english
math	math	spanish	arts	physical	spanish	spanish	religión	math	etichs
math	math	tic	spanish	biology	social	tic	social	arts	social
		Group 4					**Group 4**		
tic	math	math	arts	spanish	english	biology	biology	etichs	social
tic	math	social	math	tic	arts	social	english	math	biology
religión	etichs	social	physical	social	biology	spanish	english	social	spanish
math	spanish	biology	biology	english	religión	english	physical	spanish	spanish
biology	spanish	spanish	spanish	biology	math	math	spanish	physical	math
english	physical	english	english	etichs	math	tic	tic	tic	etichs
		Group 5					**Group 5**		
math	biology	tic	english	spanish	etichs	etichs	religión	english	english
spanish	physical	spanish	english	spanish	tic	math	math	biology	social
biology	math	english	religión	etichs	math	math	biology	tic	biology
physical	spanish	social	social	biology	english	physical	biology	spanish	spanish
tic	arts	math	math	english	social	tic	english	spanish	spanish
social	etichs	math	biology	tic	spanish	social	physical	math	arts
		Group 6					**Group 6**		
religión	english	english	tic	physical	physical	tic	social	tic	etichs
physical	english	tic	biology	spanish	etichs	biology	tic	math	spanish
math	tic	biology	math	math	spanish	biology	spanish	math	math
social	biology	spanish	math	math	math	spanish	spanish	social	social
spanish	biology	etichs	etichs	social	biology	math	biology	physical	english
spanish	arts	social	spanish	english	arts	english	religión	english	english
		Group 7					**Group 7**		
english	tic	biology	math	biology	tic	english	spanish	biology	physical
social	math	math	biology	social	social	arts	social	biology	biology
biology	math	spanish	social	english	social	biology	religión	english	spanish

spanish	english	religión	spanish	etichs	spanish	etichs	math	english	spanish
spanish	physical	physical	arts	tic	math	tic	english	spanish	tic
tic	spanish	group d	english	math	math	math	group d	physical	math
		Group 8					**Group 8**		
physical	english	math	biology	english	social	math	math	spanish	english
english	english	spanish	arts	social	social	biology	etichs	religión	english
tic	social	biology	social	biology	math	group d	tic	tic	biology
math	math	etichs	tic	spanish	biology	spanish	spanish	tic	biology
math	spanish	religión	spanish	math	english	english	arts	math	spanish
biology	tic	group d	spanish	physical	physical	physical	social	math	spanish
		Group 9					**Group 9**		
spanish	biology	english	physical	religión	math	spanish	social	math	social
biology	biology	biology	math	math	math	spanish	english	physical	spanish
group d	spanish	math	spanish	spanish	spanish	math	spanish	biology	religión
english	social	spanish	english	social	physical	english	biology	group d	english
tic	math	arts	tic	etichs	social	biology	arts	tic	math
physical	math	social	tic	english	tic	biology	etichs	english	tic
		Group 10					**Group 10**		
spanish	math	social	social	social	biology	biology	biology	religión	tic
english	english	english	group d	english	biology	arts	math	math	tic
arts	spanish	tic	tic	religión	spanish	math	etichs	spanish	social
etichs	spanish	math	biology	spanish	english	spanish	spanish	social	spanish
biology	biology	math	math	spanish	english	physical	physical	english	math
math	biology	physical	physical	tic	math	social	tic	group d	english
		Group 11					**Group 11**		
math	biology	spanish	arts	math	math	social	physical	english	english
spanish	math	etichs	physical	math	biology	biology	english	social	english
spanish	spanish	social	spanish	biology	religión	biology	social	math	biology
english	tic	math	english	religión	tic	tic	group d	math	math
social	tic	group d	biology	english	tic	spanish	etichs	spanish	physical
biology	physical	english	social	tic	spanish	math	spanish	spanish	arts
		Group 12					**Group 12**		
social	spanish	physical	biology	groupd	spanish	biology	biology	biology	biology
tic	spanish	math	biology	biology	physical	math	social	tic	physical
etichs	biology	math	english	math	english	math	english	spanish	tic
math	religión	english	social	english	social	english	math	spanish	etichs
physical	english	tic	social	spanish	math	spanish	tic	religión	english
spanish	math	arts	tic	spanish	group d	spanish	arts	math	social
		Group 13					**Group 13**		
philoso	spanish	electron	english	etichs	philoso	tic	spanish	physics	spanish
spanish	spanish	chemistr	math	religión	philoso	policie	chemistry	etichs	electro
english	math	english	math	policies	english	english	physics	religión	english
math	chemistr	english	chemistr	tic	english	chemistr	english	math	history
tic	english	physics	physical	tic	chemistr	physics	math	math	tic
history	philoso	physics	spanish	physics	spanish	math	physical	spanish	tic
		Group 14					**Group 14**		
math	philoso	chemistr	spanish	tic	english	philoso	math	spanish	philoso
math	chemist	spanish	etichs	tic	english	spanish	tic	physics	chemistr
chemistr	physical	spanish	physics	spanish	physics	history	english	math	math
philoso	physics	electro	religión	english	physic	religión	electro	etichs	physical
english	history	english	english	english	math	tic	spanish	english	english
physics	math	tic	math	policies	policies	tic	chemistr	chemistr	spanish

Group 15					Group 15				
chemistr	history	math	etichs	electro	chemistr	religión	philoso	physical	electro
chemistr	policie	math	tic	spanish	spanish	tic	physics	chemistr	policie
english	tic	english	chemistr	philoso	math	tic	math	etichs	physics
spanish	math	spanish	philoso	physics	philoso	physics	english	english	english
physics	physics	spanish	english	physical	tic	spanish	english	history	spanish
tic	english	religión	english	math	english	chemistr	spanish	math	math
Group 16					**Group 16**				
english	etichs	tic	physics	spanish	math	spanish	tic	history	physics
physics	math	philoso	electro	math	english	english	spanish	electro	spanish
physics	english	math	spanish	math	chemistr	english	chemistr	english	physical
policie	english	history	spanish	physical	chemistr	math	policies	religión	math
spanish	tic	english	tic	philoso	spanish	math	physics	physics	philoso
religión	chemistr	chemistr	chemistr	english	tic	etichs	english	tic	philoso

5 Conclusions

The results show that the methodology developed achieves an improvement of 12.3% in the assigning of class schedules based on the model of student learning rhythms when compared to the CS, program currently used by the school under study. Additionally, the algorithm shows high stability in the found solutions, ensuring an efficiency of over 92%, (Tables 4 and 5) in the results obtained in each cycles. Finally, this methodology is to be implemented as a future line of research in a large number of schools in order to analyze its impact.

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