

APPLYING ILS ALGORITHM WITH A NEW NEIGHBORHOOD OPERATOR TO SOLVE A LARGE BENCHMARK OF THE HIGH SCHOOL TIMETABLING PROBLEM

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ABSTRACT

This paper introduces a new benchmark dataset¹ to the high school timetabling problem (HSTP) with more than one hundred instances taken from Brazilian high schools. To solve the problem, our approach makes use of Iterated Local Search (ILS) metaheuristic. The black-box heuristic of ILS incorporates a Steepest Descent (SD) procedure running a new problem dependent neighborhood operator. Then we give details about the benchmark dataset and present the best solutions found by ILS algorithm.

KEYWORDS. High school timetabling benchmark, ILS, Neighborhood operator.

Main area: OR in Education, Metaheuristics, Combinatorial Optimization.

¹ This benchmark dataset will be freely available at this website <http://www.din.uem.br/gpea/benchmark/> as soon as we conclude it.

1. Introduction

Timetabling is a hard combinatorial optimization problem taking into account the computational complexity theory, on the other hand, it is NP-Complete and in general, it is tackled heuristically. The most known real world timetabling problem is faced in educational institutions. In this context, the timetabling problem can be classified into three main categories: High School Timetabling, Course Timetabling and Examination Timetabling. They differ from each other based on the type of institutions involved (Schaerf, 1999a).

High School Timetabling: the scheduling of lessons sharing teacher-class pairs over a timetable with a fixed number of timeslots during the week. In some situations, institutions still have to take into account the scheduling of rooms.

Course Timetabling: the scheduling of university courses lessons sharing common students and sometimes rooms, over a timetable with a fixed number of timeslots.

Examination Timetabling: the scheduling for the exams of a set of university courses having students in common.

Usually the timetabling problem is solved manually by experts in the majority of the educational institutions that faces with it, and in practice the solutions obtained are not so good. Moreover, a handmade timetable can take several days to be accomplished and due to frequent changes in the resources requirements, i.e. teachers who leave the school, it has to be remade, engendering serious inconvenient on the institution normal diary activities. For these reasons, to timetable manually a scheduling is a hard task.

Due to the above stated, more attention have been devoted to automated timetabling during the last forty years by academic researchers. In special, in the last two decades a large number of experimental papers tackling the problem by metaheuristics have been introduced at the literature. To a detailed review about techniques to solve educational timetabling problems the reader can see (Schaerf, 1999a) and (Pillay, 2010).

On the other hand, the researches in educational timetabling field have only grown in course timetabling and examination timetabling. No much effort has been devoted to develop the researches in the high school timetabling problem. The research in this domain, during the last decades, has been too fragmented (Post et al., 2008, 2010)² and (Pillay, 2010). As described by these authors, the main critical barrier in this area is due to isolated studies addressing no common school problems, consequently, no significant high school timetabling benchmarks have been built and used to experimentally compare different algorithms performance.

In this paper we present a new school timetabling benchmark dataset based on various real cases of Brazilian high schools. In addition, an ILS algorithm with a new neighborhood operator is proposed to solve the dataset of instances and the best results are shown. Then, since this benchmark may be available online, researchers would be able to share it to test their algorithms and perform comparative studies by comparing their results with previous one.

The paper is organized as follows: Section 2 defines the HSTP studied and presents a simplified mathematical model³ to it, we name this model as our elementary HSTP and use it to define the new neighborhood. Section 3 shows the solutions approach, explains the basic ILS algorithm, the new neighborhood operator and the computational solution representation. Section 4 describes some details about our benchmark dataset. Section 5 depicts the best results obtained running the ILS algorithm. Finally, section 6 provides a summary and futures extensions.

2. Problem definition

The HSTP defined in this paper is based on thirteen Brazilian high schools. Thus, in order to get a general problem definition we take into account only those common constraints among these schools. The HSTP can be defined as follows: all school activities are spread into five days over the week, and each activity day is divided into three shifts with five lesson periods

² These authors have proposed the benchmarking project for high school timetabling in PATAT 2008.

³ This model is a simple HSTP version and considers only our hard constraints, it was adapted from (Schaerf, 1999a) and can be solved in polynomial time.

each. Then, a timetable refers to a schedule of all lessons in a given shift. Classes are disjoint groups of students having the same subjects; each subject for each class is taught by only one teacher and it is previous defined by the school; all classes have no idle time periods during the week; classrooms are predefined and not considered in the scheduling. The most of the teachers are not full time at school, because they are shared with other schools, thus teachers availability have to be considered. A useful timetable must satisfy the hard constraints to be feasible and optimize the soft constraints.

Let $H = \{H_1, H_2, H_3\}$ be the set of hard constraints defined as follows:

H_1 : all lessons of classes and teachers must be scheduled; H_2 : a class must attends a lesson with only one teacher by period; H_3 : a teacher must teaches only one class by period;

Let $S = \{S_1, S_2, S_3, S_4, S_5, S_6, S_7\}$ be the set of soft constraints defined as below:

S_1 : teachers' availability must be respected; S_2 : a class must be scheduled to attend at most two lessons with a same teacher by day; S_3 : teacher-class' lessons must not be disjoint on the same day; S_4 : teacher-class' consecutive double lessons requirements have to be satisfied as far as possible; S_5 : teachers must have as few idle times as possible, unavailable periods between two lessons on a day are not considered as idle time; S_6 : teachers' weekly agenda has to be as compact as possible; S_7 : the compactness in teachers' agenda has to be balanced among them;

Definition 1 expresses our elementary HSTP. Namely, the HSTP is feasible if the mathematical model in definition 1 is satisfied:

Definition 1: The HSTP is feasible if the following mathematical model is satisfied:

Let us denote by $T = \{1, \dots, nt\}$ the set of teachers who teaches the set $C = \{1, \dots, nc\}$ of classes at school in a given shift, during $D = \{1, \dots, nd\}$ days, with each day composed by a set $P = \{1, \dots, np\}$ of periods, in which $nd = np = 5$ is fixed. In addition, let us consider the predefined requirement matrix $R_{|T| \times |C|}$, where r_{tc} is the number of lessons given by teacher t to class c . The elementary HSTP can be formulated as follows:

Find x_{tcdp} ($t = 1..nt; c = 1..nc; d = 1..nd; p = 1..np$):

Subject to:

$$\sum_{d=1}^{nd} \sum_{p=1}^{np} x_{tcdp} = r_{tc} \quad (t = 1..nt; c = 1..nc) \quad (H_1)$$

$$\sum_{t=1}^{nt} x_{tcdp} = 1 \quad (c = 1..nc; d = 1..nd; p = 1..np) \quad (H_2)$$

$$\sum_{c=1}^{nc} x_{tcdp} \leq 1 \quad (t = 1..nt; d = 1..nd; p = 1..np) \quad (H_3)$$

$$x_{tcdp} \in \{0, 1\}$$

Where $x_{tcdp} = 1$ if teacher t and class c meet at period p of day d , and $x_{tcdp} = 0$ otherwise. Constraints H_1 , H_2 and H_3 are those aforementioned.

The key ingredient of the new neighborhood operator introduced in section 3.2 is that it is capable to exclude out of the search space, every solution that does not satisfy the elementary HSTP. In other words, every neighbor generated by this neighborhood operator is a feasible solution.

To tackle the HSTP heuristically the solution approach must to be defined. Then the next section presents: the solution representation structure, the procedure used to generate initial solutions, the new neighborhood operator, the objective function and the ILS algorithm employed to solve the problem.

3. Solution approach

3.1 Solution representation and initial solution

A HSTP solution is represented by a non-negative integer three-dimensional matrix $Z_{|C|\times|D|\times|P|}$, where a cell z_{cdp} stores the teacher t who teaches class c during period p on day d .

In this representation one has not to take care of constraints H_1 and H_2 , they are automatically satisfied. As initial solution, a random timetable Z_0 is used. It is generated by using a procedure that randomly selects each teacher-class' lesson in $R_{|T|\times|C|}$ and schedules it in Z_0 .

3.2 Neighborhood operator

One of the most critical features on the development of local search heuristics is the definition of the neighborhood operators (Di Gaspero and Schaerf, 2006). This aspect have been considered by several authors (Van Laarhoven; Aarts and Lenstra, 1992), (Dell'Amico and Trubian, 1993), (Kaneko; Yoshikawa and Nakakuki, 1999), (Schaerf, 1999b), (Osogami and Imai, 2000), (Melicio; Caldeira and Rosa, 2004), (Souza; Moretti and Podestá, 2008) and (Zhang, et al., 2010). The main aim they take into account are the development of powerful neighborhood operators so that local search heuristics using it, might be able to efficiently search the solution space of the optimization problem.

Van Laarhoven, Aarts and Lenstra (1992); Dell'Amico and Trubian (1993) and in special Osogami and Imai (2000) introduced the following empirical proposition: "as some constraints have higher priority, then only a limited subset of solutions satisfying these constraints in the solution space contains good solutions". Besides, they demonstrated that for some optimization problems are possible to construct operators able to navigate only over this restricted subset of solutions and such the local search algorithm using it, can efficiently explores the search space. They apply it in job shop scheduling and nurse scheduling problems.

Every HSTP neighborhood operators that we have found at the literature have the following deficiency: given a feasible solution of the HSTP, a large number of neighbors into the neighborhood generated by these operators are infeasible solutions with teacher or class overlaps.

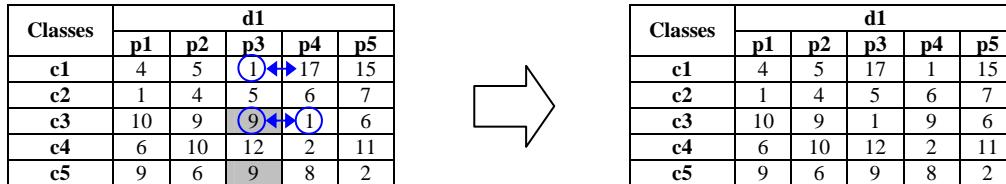
Some efforts have been made to turn around this issue. One technique that have been employed by some researchers as (Schaerf, 1999b), (Kaneko; Yoshikawa and Nakakuki, 1999) and (Souza; Moretti and Podestá, 2008) is to use *repair methods* to try to repair a solution when an operator generates an infeasible solution, but no known operator is able to completely repair the generated infeasible solutions. In our neighborhood operator this matter is prevented making use of Osogami-Imai's proposition. Namely, given a feasible solution satisfying the elementary HSTP, any local search heuristic using this operator is capable to navigate only over the subset of feasible solutions (definition 1). Below in definition 2, we define the classical double move neighborhood operator used in timetabling problems. Our neighborhood (definition 3) is based on this classical neighborhood.

Definition 2: Given a timetable Z , an arbitrary class c , days d_1 and d_2 , periods p_1 and p_2 , where $Z[c, d_1, p_1] = t_1$ and $Z[c, d_2, p_2] = t_2$ with $t_1 \neq t_2$. The **double move operator** consists in perform the following operations in the timetable: $Z[c, d_1, p_1] = t_2$ and $Z[c, d_2, p_2] = t_1$.

Definition 3: Apply a **double move operator** in $Z[c_k, d_1, p_1] = (t_1)_k$ and $Z[c_k, d_2, p_2] = (t_2)_k$. If this move generates new teacher overlaps, say in classes c_i and c_j ($c_k, c_i, c_j \in C$ and $k \neq i \neq j$). Then, performs a chain of double moves swapping those pairs of cells on classes c_i and c_j over periods p_1 and p_2 , and repeating it until no new overlaps occur.

Our operator has two advantages. First, we can use it to converge from a non-feasible solution to a feasible one, applying the operator to reallocate those overlapping teachers to periods in which they are not allocated, as in figure 1. Second, we can navigate from a feasible

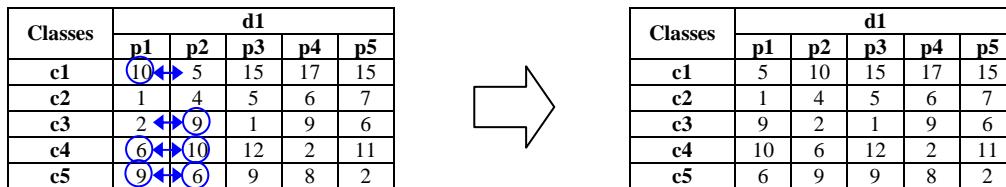
solution to another (figure 2). In figure 2, the operator starting with class c5, generates two new overlappings in c3 and c4, so applying a double move to repair these overlappings, a new overlapping is generated in c1, but applying to it the double move again, a new feasible solution is reached. Although not demonstrated here, this operator can be implemented in $O(|C|^2)$ complexity and in the worst case it will swaps the teachers on two periods p_1 and p_2 , for every class $c \in C$.



Classes	d1				
	p1	p2	p3	p4	p5
c1	4	5	1	17	15
c2	1	4	5	6	7
c3	10	9	9	1	6
c4	6	10	12	2	11
c5	9	6	9	8	2

Classes	d1				
	p1	p2	p3	p4	p5
c1	4	5	17	1	15
c2	1	4	5	6	7
c3	10	9	1	9	6
c4	6	10	12	2	11
c5	9	6	9	8	2

Figure 1: Converging from a non-feasible solution to a feasible one



Classes	d1				
	p1	p2	p3	p4	p5
c1	10	5	15	17	15
c2	1	4	5	6	7
c3	2	9	1	9	6
c4	6	10	12	2	11
c5	9	6	9	8	2

Classes	d1				
	p1	p2	p3	p4	p5
c1	5	10	15	17	15
c2	1	4	5	6	7
c3	9	2	1	9	6
c4	10	6	12	2	11
c5	6	9	9	8	2

Figure 2: Navigating from a feasible solution to another

3.3 Objective function

A solution Z is evaluated according to the following objective function:

$$f(Z) = \alpha_{H_3} \beta_{H_3} + \sum_{S_i \in S} \alpha_{S_i} \beta_{S_i} \quad (1)$$

Where the first sum measures the infeasibility level and the second one measures the level of satisfaction regarding to the soft constraints. The weight α_{H_3} (resp. α_{S_i}) reflects the relative importance of minimizing the amount of violations β_{H_3} (resp. β_{S_i}) of the constraint H_3 in H (resp. S_i in S). Thus, a feasible timetable must have $\alpha_{H_3} \beta_{H_3} = 0$.

The way that the variable β_{H_3} (resp. β_{S_i}) is evaluated is:

β_{H_3} : sum of lessons for teachers on periods they have been assigned more than once.

β_{S_i} : sum of designed periods for teachers in which they are unavailable to teach;

β_{S_2} : sum of the number of lessons deducted by two units for teacher-class pairs on days they have been assigned more than two times;

β_{S_3} : sum of the number of lessons for teacher-class pairs on days, if the lessons are disjoint on these days;

β_{S_4} : sum of the non-negative difference between the minimum number of double lessons required by teacher-class pairs and the effective number of double lessons in their current agenda.

β_{S_5} : sum of the number of idle times on teachers' agenda.

β_{S_6} : sum for teachers of the difference between the number of scheduled days and the minimum one possible.

β_{S_7} : the standard deviation considering the difference in β_{S_i} for all teachers.

3.4 Iterated Local Search algorithm

Our ILS algorithm is a simple version that in (Lourenço, Martin and Stützle, 2003). The

basic idea of ILS is to explore solutions by performing a walk over the search space stepping from one local minimum to another, that to a new one, and so on. Taking an initial solution Z_0 , ILS algorithm runs a slave local search heuristic to getting stuck in a local minimum Z^* . Then iteratively, it applies a perturbation procedure to jump out of the local minimum and performs a new execution of the local search heuristic to reach another local minimum $Z^{* \prime}$, if it passes the acceptance test, it will be perturbed in the next iteration, otherwise returns to Z^* . Figure 3 shows the basic ILS procedure. The reader can see a detailed review about iterated local search in (Lourenço, Martin and Stützle, 2003). ILS is a modular algorithm and the main modules are: GenerateInitialSolution, LocalSearch, Perturbation and AcceptanceCriterion.

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procedure ILS( )
     $Z_0 = \text{GenerateInitialSolution}$ 
     $Z^* = \text{LocalSearch}(Z_0)$ 
    repeat
         $Z' = \text{Perturbation}(Z^*)$ 
         $Z^{* \prime} = \text{LocalSearch}(Z')$ 
         $Z^* = \text{AcceptanceCriterion}(Z^*, Z^{* \prime})$ 
    until (stop criterion met)
end

```

Figure 3: The basic ILS algorithm

In our implementation we use random initial solutions as described in section 3.1, as a local search a steepest descent (SD) heuristic incorporating the new neighborhood operator explained in section 3.2 is employed, this heuristic repeatedly replaces the current solution by the first improvement in its neighborhood until no improvement is possible. The perturbation procedure makes use of two random moves using the neighborhood operator defined in section 3.2. Finally, the acceptance test selects only better solutions.

To solve the HSTP we apply ILS algorithm in two phases: at the first phase only constraints H_3 and S_1 are inserted into the objective function. When ILS gets $f(Z) = \alpha_{H_3}\beta_{H_3} + \alpha_{S_1}\beta_{S_1} = 0$, the second phase proceeds considering only $f(Z) = \sum_{S_i \in S} \alpha_{S_i}\beta_{S_i}$ as the objective function to be minimized. This is because the neighborhood operator always satisfies definition 1, and the objective function has not to take control over H_3 constraint in this phase.

4. Proposed high school timetabling benchmark dataset

The benchmark dataset is composed by 102 instances of the HSTP, 34 are real world and 68 are semi-real world instances, it means they are real world cases with some modifications. The instances are classified into three groups with 34 instances each. The main goal is to create three levels of hardness to solve the problem. To accomplish this, we have used the concept of sparseness ratio $sr = \left(1 - \frac{NL + UP}{|T| \times |D| \times |P|}\right)$ introduced by (Souza; Ochi and Maculan, 2003), where

NL represents the total number of lessons to be scheduled, UP is the total unavailable periods of teachers and $|T|$, $|D|$ and $|P|$ are respectively, the number of teachers, days and periods in the timetable. This expression is a measure of how many is the timetabling constrained in terms of unavailable periods. Lower values indicate a harder problem and higher values a flexible problem. Since this expression has *lower* and *upper* bound values, the three groups are:

Real Sparseness Group: this group includes those 34 pure real world instances and the sparseness ratio ranges between *lower* and *upper* values.

Maximum Sparseness Group: this group is a copy of the first one with all teachers'

unavailable periods set to free, thus the sparseness ratio for all instances has *upper* value, making a timetable more flexible to solve.

Table 1: Characteristics of the instances

ID	Instance	Classes	Teachers	Days	Periods	N. of Lessons	Minimum of Required Double Lessons	I.C.S.
1	CL-CEASD-2008-V-A	12	27	5	5	300	132	72
2	CL-CEASD-2008-V-B	12	27	5	5	300	132	72
3	CL-CECL-2011-M-A	13	32	5	5	325	144	76
4	CL-CECL-2011-M-B	13	34	5	5	325	143	77
5	CL-CECL-2011-N-A	9	30	5	5	225	107	59
6	CL-CECL-2011-V-A	14	35	5	5	350	164	83
7	CM-CECM-2011-M	20	51	5	5	500	234	123
8	CM-CECM-2011-N	8	30	5	5	200	96	52
9	CM-CECM-2011-V	13	34	5	5	325	142	79
10	CM-CEDB-2010-N	5	17	5	5	125	60	32
11	CM-CEUP-2008-V	16	35	5	5	400	192	94
12	CM-CEUP-2011-M	16	38	5	5	400	192	96
13	CM-CEUP-2011-N	3	15	5	5	75	36	24
14	CM-CEUP-2011-V	16	34	5	5	400	169	95
15	FA-EEF-2011-M	4	12	5	5	100	42	25
16	JNS-CEDPII-2011-M	8	19	5	5	200	85	49
17	JNS-CEDPII-2011-V	7	21	5	5	175	73	47
18	JNS-CEJXXIII-2011-M	5	18	5	5	125	60	32
19	JNS-CEJXXIII-2011-N	4	15	5	5	100	48	27
20	JNS-CEJXXIII-2011-V	5	18	5	5	125	60	30
21	MGA-CEDC-2011-M	19	38	5	5	475	210	111
22	MGA-CEDC-2011-V	12	33	5	5	300	131	73
23	MGA-CEGV-2011-M	31	62	5	5	775	352	182
24	MGA-CEGV-2011-V	32	75	5	5	800	357	195
25	MGA-CEJXXIII-2010-V	16	35	5	5	400	192	94
26	MGA-CEVB-2011-M	10	21	5	5	250	108	60
27	MGA-CEVB-2011-V	9	20	5	5	225	97	56
28	NE-CESVP-2011-M-A	18	45	5	5	450	212	111
29	NE-CESVP-2011-M-B	18	44	5	5	450	212	111
30	NE-CESVP-2011-M-C	18	45	5	5	450	211	109
31	NE-CESVP-2011-M-D	18	45	5	5	450	211	109
32	NE-CESVP-2011-V-A	16	44	5	5	400	183	101
33	NE-CESVP-2011-V-B	16	43	5	5	400	184	100
34	NE-CESVP-2011-V-C	16	43	5	5	400	182	100

Table 2: Characteristics of each group of instances

ID	Real		Maximum		Minimum		17	101	0,47	0	0,67	350	0,00
	U.P.	S.R.	U.P.	S.R.	U.P.	S.R.							
1	108	0,40	0	0,56	375	0,00	18	50	0,61	0	0,72	325	0,00
2	108	0,40	0	0,56	375	0,00	19	12	0,70	0	0,73	275	0,00
3	23	0,57	0	0,59	475	0,00	20	52	0,61	0	0,72	325	0,00
4	8	0,61	0	0,62	525	0,00	21	399	0,08	0	0,50	475	0,00
5	25	0,67	0	0,70	525	0,00	22	446	0,10	0	0,64	525	0,00
6	25	0,57	0	0,60	525	0,00	23	588	0,12	0	0,50	775	0,00
7	648	0,10	0	0,61	775	0,00	24	857	0,12	0	0,57	1075	0,00
8	489	0,08	0	0,73	550	0,00	25	309	0,19	0	0,54	475	0,00
9	455	0,08	0	0,62	525	0,00	26	167	0,21	0	0,52	275	0,00
10	41	0,61	0	0,71	300	0,00	27	214	0,12	0	0,55	275	0,00
11	345	0,15	0	0,54	475	0,00	28	156	0,46	0	0,60	675	0,00
12	498	0,05	0	0,58	550	0,00	29	167	0,44	0	0,59	650	0,00
13	284	0,04	0	0,80	300	0,00	30	153	0,46	0	0,60	675	0,00
14	382	0,08	0	0,53	450	0,00	31	267	0,36	0	0,60	675	0,00
15	160	0,13	0	0,67	200	0,00	32	181	0,47	0	0,64	700	0,00
16	91	0,39	0	0,58	275	0,00	33	192	0,45	0	0,63	675	0,00
							34	218	0,43	0	0,63	675	0,00

Minimum Sparseness Group: this group is a copy of the second, and the set of unavailable periods for each instance was built as follows: for each instance in the second group i) choose the best solution found by the ILS algorithm; ii) select all periods without activity in the teachers' agenda over the best solution; iii) set them unavailable to the corresponding instance copy in the third group. The main goal of this strategy was to build an instances group with a high level of hardness to solve, but with good solutions known. Furthermore, it makes us sure

that it is possible to obtain a good solution attending all teachers' unavailable periods for any instance in this group. On the other hand, the instances in this group have minimum sparseness ratio.

We believe that this benchmark dataset extracts a reasonable sample of the HSTP faced at Brazilian high schools, to see why, we refer to the works of (Souza; Ochi; Maculan, 2003) and (Souza; Moretti; Podestá, 2008), they tackle similar problems at other high schools from different places in Brazil. In our benchmark dataset, the instances have a diversity of characteristics in terms of dimensions and hardness to solve: number of classes ranging (from 3 to 32), number of teachers (from 12 to 75) and sparseness ratio in three levels of difficulty. So, it is a good scenery to test new algorithms to the HSTP. Table 1 depicts all common characteristics of the instances and table 2 those uncommon characteristics among them. Where "I.C.S." column is the sum of activity days for teachers, if the timetable was ideal compactness schedule, namely, if it was a maximum compactness schedule. The column labeled with "U.P." shows the total number of teachers' unavailable periods, and the "S.R." column shows the instance's sparseness ratio.

5. Experimental results

The proposed approach was coded using MS Visual Basic 6 and experimented over the proposed benchmark dataset on a PC machine with a dual (2) six-core Intel Xeon 2.8 GHz processor and 16 GB of RAM under Windows Server 2008 platform. Five tests were carried out for each instance in each group running five simultaneous processes of ILS algorithm during 1024 seconds on the second phase. In this experimentation the objective function was calibrated using $\alpha_{H_3} = \alpha_{S_1} = 1$ at the first phase and $\alpha_{S_1} = 10.000$, $\alpha_{S_2} = 100$, $\alpha_{S_3} = 25$, $\alpha_{S_4} = \alpha_{S_5} = \alpha_{S_6} = \alpha_{S_7} = 10$ at the second one. These weights reflect in general, the priority given by the schools to the constraints.

Tables 3, 4 and 5 summarize the results. These tables show for each instance, the best (bold line) and the average solution (next line) out of five runs of ILS. Column "Time" exhibits the time in seconds expended by ILS at the first phase. Column T.S.D shows the total number of activity days scheduled for all teachers. Column $\overline{\beta_{S_6}}$ is the average value of β_{S_6} , and the last column prints the objective function value. Finally, the other columns depict the number of violations to the remaining constraints.

As a general view, ILS algorithm was capable to obtain feasible solutions and satisfy S_1 constraint for every instance in each group. Moreover, it has obtained high performance in minimizing the soft constraints. Furthermore, the experimental results confirm our conjecture that each group of instances has distinct levels of hardness to solve them. So, ILS had more difficult to solve "real sparseness group" than "maximum sparseness group" and also, more difficult to solve "minimum sparseness group" than "real sparseness group". Although we have run ILS during 1024 seconds for each instance, strong minimizations on the objective function have occurred during the first 120 seconds of ILS execution.

6. Conclusions and future works

In this paper we have defined a generic HSTP and introduced a large benchmark dataset with instances of several Brazilian high schools. Moreover, we have proposed a new neighborhood operator and incorporated it into a SD local search to run as the black-box heuristic used by ILS algorithm. We have run this algorithm on the HSTP benchmark dataset and the results have shown that it is a competitive approach and works very well over the problem instances. It is worthy to stress, that we have investigated at the literature and no article has been found using the proposed neighborhood operator.

As future works we intend to join our set of instances to the benchmarking project for high school timetabling introduced at PATAT 2008 (Post et al., 2008, 2010). Besides, we wish to test the new neighborhood operator with other metaheuristics and compare this operator with other classical operators in the literature.

Table 3: Results to the real sparseness group

ID	Instance	Time(s)	β_{H_3}	β_{S_1}	β_{S_2}	β_{S_3}	β_{S_4}	β_{S_5}	S_6		S_7		O.F.
									T.S.D.	β_{S_6}	$\bar{\beta}_{S_6}$	β_{S_7}	
1	CL-CEASD-2008-V-A	1,00	0	0	0	0	27	13	74	2	0,07	0,26	422,62
		1,00	0	0	0	0,40	29,20	9,40	76,40	4,40	0,16	0,36	443,59
2	CL-CEASD-2008-V-B	0,00	0	0	0	0	27	8	76	4	0,15	0,36	393,55
		0,00	0	0	0	0,00	27,00	11,20	75,40	3,40	0,13	0,33	419,28
3	CL-CECL-2011-M-A	0,00	0	0	0	0	20	9	80	4	0,13	0,33	333,31
		0,00	0	0	0	0,00	27,40	10,00	79,80	3,80	0,12	0,32	415,23
4	CL-CECL-2011-M-B	0,00	0	0	0	0	25	6	80	3	0,09	0,28	342,84
		0,00	0	0	0	0,00	25,80	8,40	80,20	3,20	0,09	0,29	376,88
5	CL-CECL-2011-N-A	0,00	0	0	0	0	19	0	68	9	0,30	0,59	285,86
		0,00	0	0	0	0,00	18,80	2,00	67,40	8,40	0,28	0,58	297,78
6	CL-CECL-2011-V-A	0,00	0	0	0	0	27	8	85	2	0,06	0,23	372,32
		0,00	0	0	0	0,00	34,00	5,40	84,20	1,20	0,03	0,16	407,60
7	CM-CECM-2011-M	0,00	0	0	0	0	61	19	133	10	0,20	0,40	903,97
		0,00	0	0	0	0,40	66,00	20,40	133,60	10,60	0,21	0,44	984,42
8	CM-CECM-2011-N	1,00	0	0	0	2	25	8	69	17	0,57	0,67	556,67
		0,80	0	0	0	2,00	33,80	6,00	69,80	17,80	0,59	0,66	632,60
9	CM-CECM-2011-V	0,00	0	0	0	0	24	10	88	9	0,27	0,44	434,41
		0,00	0	0	0	0,80	31,40	13,40	87,80	8,80	0,26	0,44	560,37
10	CM-CEDB-2010-N	0,00	0	0	0	0	11	0	32	0	0,00	0,00	110,00
		0,00	0	0	0	0,00	10,80	0,00	32,40	0,40	0,02	0,09	112,94
11	CM-CEUP-2008-V	0,00	0	0	0	0	62	11	105	11	0,31	0,52	845,22
		0,00	0	0	0	0,80	65,00	10,20	106,80	12,80	0,37	0,54	905,36
12	CM-CEUP-2011-M	1,00	0	0	0	0	60	19	106	10	0,26	0,44	894,40
		1,20	0	0	0	0,40	71,40	17,60	105,60	9,60	0,25	0,43	1000,34
13	CM-CEUP-2011-N	0,00	0	0	0	0	10	3	28	4	0,27	0,44	174,42
		0,20	0	0	0	0,80	11,20	3,80	27,60	3,60	0,24	0,43	210,25
14	CM-CEUP-2011-V	4,00	0	0	0	0	38	17	99	4	0,12	0,32	593,22
		1,60	0	0	0	1,20	41,60	16,00	99,40	4,40	0,13	0,33	653,35
15	FA-EEF-2011-M	0,00	0	0	0	2	4	8	26	1	0,08	0,28	182,76
		0,00	0	0	0	2,00	4,00	7,80	26,20	1,20	0,10	0,30	182,95
16	JNS-CEDPHI-2011-M	0,00	0	0	0	0	14	2	52	3	0,16	0,37	193,65
		0,00	0	0	0	0,00	12,40	3,80	53,60	4,60	0,24	0,42	212,22
17	JNS-CEDPHI-2011-V	0,00	0	0	0	0	7	4	50	3	0,14	0,35	143,50
		0,00	0	0	0	0,00	9,00	4,80	50,20	3,20	0,15	0,36	173,59
18	JNS-CEJXXIII-2011-M	0,00	0	0	0	0	10	1	35	3	0,17	0,37	143,73
		0,00	0	0	0	0,00	11,40	2,20	35,00	3,00	0,17	0,37	169,70
19	JNS-CEJXXIII-2011-N	0,00	0	0	0	0	8	1	27	0	0,00	0,00	90,00
		0,00	0	0	0	0,00	8,40	1,20	27,00	0,00	0,00	0,00	96,00
20	JNS-CEJXXIII-2011-V	0,00	0	0	0	0	11	1	35	5	0,28	0,45	174,48
		0,00	0	0	0	0,00	10,20	2,40	34,80	4,80	0,27	0,44	178,42
21	MGA-CEDC-2011-M	1,00	0	0	0	0	57	14	113	2	0,05	0,22	732,23
		0,80	0	0	0	0,00	59,80	13,20	113,20	2,20	0,06	0,23	754,29
22	MGA-CEDC-2011-V	2,00	0	0	0	2	30	8	76	3	0,09	0,29	462,87
		4,00	0	0	0	2,00	32,60	9,80	77,00	4,00	0,12	0,32	517,24
23	MGA-CEGV-2011-M	0,00	0	0	0	0	111	28	204	22	0,36	0,48	1614,78
		0,00	0	0	0	1,20	116,80	31,00	201,20	19,20	0,31	0,46	1704,60
24	MGA-CEGV-2011-V	0,00	0	0	0	2	88	33	222	27	0,36	0,48	1534,80
		0,20	0	0	0	1,20	100,60	31,60	222,00	27,00	0,36	0,48	1626,80
25	MGA-CEJXXIII-2010-V	0,00	0	0	0	0	50	10	101	7	0,20	0,47	674,66
		0,00	0	0	0	0,40	56,80	8,80	101,80	7,80	0,22	0,46	748,64
26	MGA-CEVB-2011-M	0,00	0	0	0	0	18	5	63	3	0,14	0,35	263,50
		0,00	0	0	0	0,00	19,60	5,60	63,20	3,20	0,15	0,36	287,59
27	MGA-CEVB-2011-V	0,00	0	0	0	0	16	3	60	4	0,20	0,40	234,00
		0,00	0	0	0	0,00	17,00	4,20	60,00	4,00	0,20	0,40	256,00
28	NE-CESVP-2011-M-A	0,00	0	0	0	0	41	16	121	10	0,22	0,47	674,66
		0,00	0	0	0	0,00	42,80	15,20	123,60	12,60	0,28	0,49	710,94
29	NE-CESVP-2011-M-B	0,00	0	0	0	0	42	14	123	12	0,27	0,49	684,94
		0,00	0	0	0	0,40	42,20	15,20	122,80	11,80	0,27	0,51	707,08
30	NE-CESVP-2011-M-C	0,00	0	0	1	0	48	11	124	15	0,33	0,47	844,71
		0,00	0	0	1	0,00	48,20	16,20	124,80	15,80	0,35	0,53	907,26
31	NE-CESVP-2011-M-D	0,00	0	0	0	0	45	9	125	16	0,36	0,52	705,23
		0,00	0	0	0	0,40	46,80	13,40	124,60	15,60	0,35	0,54	773,35
32	NE-CESVP-2011-V-A	0,00	0	0	0	0	31	15	113	12	0,27	0,49	584,94
		0,00	0	0	0	0,00	35,20	14,00	112,80	11,80	0,27	0,45	614,51
33	NE-CESVP-2011-V-B	0,00	0	0	0	0	31	13	111	11	0,26	0,49	554,87
		0,00	0	0	0	0,00	33,80	13,40	112,00	12,00	0,28	0,50	596,97
34	NE-CESVP-2011-V-C	0,00	0	0	0	0	31	16	113	13	0,30	0,51	605,07
		0,00	0	0	0	0,00	34,40	17,80	111,80	11,80	0,27	0,50	645,03

Table 4: Results to the maximum sparseness group

ID	Instance	Time(s)	β_{H_3}	β_{S_1}	β_{S_2}	β_{S_3}	β_{S_4}	β_{S_5}	S_6		S_7		O.F.
									T.S.D.	β_{S_6}	$\bar{\beta}_{S_6}$	β_{S_7}	
1	CL-CEASD-2008-V-A	1,00	0	0	0	0	21	2	76	4	0,15	0,36	273,55
		1,00	0	0	0	0,00	23,00	5,20	75,40	3,40	0,13	0,33	319,28
2	CL-CEASD-2008-V-B	0,00	0	0	0	0	24	4	74	2	0,07	0,26	302,62
		0,00	0	0	0	0,00	21,80	7,40	75,00	3,00	0,11	0,31	325,10
3	CL-CECL-2011-M-A	0,00	0	0	0	0	23	9	81	5	0,16	0,36	373,63
		0,00	0	0	0	0,00	24,80	10,20	80,20	4,20	0,13	0,33	395,33
4	CL-CECL-2011-M-B	0,00	0	0	0	0	24	6	80	3	0,09	0,28	332,84
		0,00	0	0	0	0,00	25,20	7,40	80,00	3,00	0,09	0,28	358,82
5	CL-CECL-2011-N-A	0,00	0	0	0	0	17	1	67	8	0,27	0,51	265,12
		0,00	0	0	0	0,00	18,20	3,20	67,00	8,00	0,27	0,51	299,12
6	CL-CECL-2011-V-A	0,00	0	0	0	0	27	5	84	1	0,03	0,17	331,67
		0,00	0	0	0	0,00	34,00	5,60	83,60	0,60	0,02	0,10	403,00
7	CM-CECM-2011-M	0,00	0	0	0	0	46	11	130	7	0,14	0,34	643,44
		0,00	0	0	0	0,40	54,60	12,60	129,80	6,80	0,13	0,34	753,38
8	CM-CECM-2011-N	0,00	0	0	0	0	16	5	57	5	0,17	0,37	263,73
		0,00	0	0	0	0,00	17,40	4,80	57,60	5,60	0,19	0,39	281,88
9	CM-CECM-2011-V	0,00	0	0	0	0	24	4	84	5	0,15	0,35	333,54
		0,00	0	0	0	0,00	24,20	5,60	84,00	5,00	0,15	0,35	351,52
10	CM-CEDB-2010-N	0,00	0	0	0	0	10	0	32	0	0,00	0,00	100,00
		0,00	0	0	0	0,00	10,20	0,60	32,00	0,00	0,00	0,00	108,00
11	CM-CEUP-2008-V	0,00	0	0	0	0	43	10	95	1	0,03	0,17	541,67
		0,00	0	0	0	0,00	44,00	10,40	96,60	2,60	0,07	0,27	572,67
12	CM-CEUP-2011-M	0,00	0	0	0	0	45	7	98	2	0,05	0,22	542,23
		0,00	0	0	0	0,00	46,80	9,60	99,00	3,00	0,08	0,26	596,65
13	CM-CEUP-2011-N	0,00	0	0	0	0	7	0	24	0	0,00	0,00	70,00
		0,00	0	0	0	0,00	7,00	0,00	24,00	0,00	0,00	0,00	70,00
14	CM-CEUP-2011-V	0,00	0	0	0	0	29	8	98	3	0,09	0,28	402,84
		0,00	0	0	0	0,00	29,40	10,40	99,40	4,40	0,13	0,33	445,30
15	FA-EEF-2011-M	0,00	0	0	0	0	2	4	28	3	0,25	0,43	94,33
		0,00	0	0	0	0,00	4,20	7,20	26,80	1,80	0,15	0,38	135,82
16	JNS-CEDPHI-2011-M	0,00	0	0	0	0	9	4	51	2	0,11	0,31	153,07
		0,00	0	0	0	0,00	11,60	6,00	50,20	1,20	0,06	0,24	190,40
17	JNS-CEDPHI-2011-V	0,00	0	0	0	0	7	4	50	3	0,14	0,35	143,50
		0,00	0	0	0	0,00	9,40	5,00	50,00	3,00	0,14	0,35	177,50
18	JNS-CEJXXIII-2011-M	0,00	0	0	0	0	10	0	34	2	0,11	0,31	123,14
		0,00	0	0	0	0,00	10,60	0,60	33,80	1,80	0,10	0,30	132,97
19	JNS-CEJXXIII-2011-N	0,00	0	0	0	0	8	1	27	0	0,00	0,00	90,00
		0,00	0	0	0	0,00	8,00	1,20	27,00	0,00	0,00	0,00	92,00
20	JNS-CEJXXIII-2011-V	0,00	0	0	0	0	10	0	35	5	0,28	0,45	154,48
		0,00	0	0	0	0,00	10,40	0,80	34,60	4,60	0,26	0,44	162,35
21	MGA-CEDC-2011-M	0,00	0	0	0	0	40	7	112	1	0,03	0,16	481,60
		0,00	0	0	0	0,00	44,80	10,80	111,80	0,80	0,02	0,11	565,09
22	MGA-CEDC-2011-V	0,00	0	0	0	0	23	9	75	2	0,06	0,24	342,39
		0,00	0	0	0	0,00	23,80	8,80	75,60	2,60	0,08	0,27	354,66
23	MGA-CEGV-2011-M	0,00	0	0	0	0	81	19	189	7	0,11	0,32	1073,16
		0,00	0	0	0	0,00	86,60	18,20	188,80	6,80	0,11	0,31	1119,12
24	MGA-CEGV-2011-V	0,00	0	0	0	0	69	19	208	13	0,17	0,41	1014,12
		0,00	0	0	0	0,00	76,60	21,80	206,20	11,20	0,15	0,36	1099,63
25	MGA-CEJXXIII-2010-V	0,00	0	0	0	0	43	8	97	3	0,09	0,37	543,68
		0,00	0	0	0	0,00	44,60	8,00	97,60	3,60	0,10	0,35	565,52
26	MGA-CEVB-2011-M	0,00	0	0	0	0	16	2	62	2	0,10	0,29	202,94
		0,00	0	0	0	0,00	17,00	3,20	62,20	2,20	0,10	0,31	227,05
27	MGA-CEVB-2011-V	0,00	0	0	0	0	12	2	59	3	0,15	0,36	173,57
		0,00	0	0	0	0,00	13,80	2,00	59,00	3,00	0,15	0,36	191,57
28	NE-CESVP-2011-M-A	0,00	0	0	0	0	40	15	122	11	0,24	0,52	665,23
		0,00	0	0	0	0,40	42,00	15,80	122,80	11,80	0,26	0,50	710,96
29	NE-CESVP-2011-M-B	0,00	0	0	0	0	37	10	122	11	0,25	0,53	585,28
		0,00	0	0	0	0,00	39,60	12,20	122,00	11,00	0,25	0,49	632,92
30	NE-CESVP-2011-M-C	0,00	0	0	0	0	36	11	123	14	0,31	0,55	615,51
		0,00	0	0	0	0,00	40,00	13,80	123,20	14,20	0,32	0,53	685,34
31	NE-CESVP-2011-M-D	0,00	0	0	0	0	39	15	123	14	0,31	0,55	685,51
		0,00	0	0	0	0,00	43,00	15,20	123,40	14,40	0,32	0,55	731,53
32	NE-CESVP-2011-V-A	0,00	0	0	0	0	28	10	113	12	0,27	0,45	504,45
		0,00	0	0	0	0,00	33,40	14,00	110,60	9,60	0,22	0,42	574,22
33	NE-CESVP-2011-V-B	0,00	0	0	0	0	28	17	110	10	0,23	0,47	554,74
		0,00	0	0	0	0,00	32,00	16,60	110,00	10,00	0,23	0,47	590,74
34	NE-CESVP-2011-V-C	0,00	0	0	0	0	30	14	111	11	0,26	0,49	554,87
		0,00	0	0	0	0,00	31,40	16,80	109,60	9,60	0,22	0,47	582,68

Table 5: Results to the minimum sparseness group

ID	Instance	Time(s)	β_{H_3}	β_{S_1}	β_{S_2}	β_{S_3}	β_{S_4}	β_{S_5}	S_6		S_7		O.F.
									T.S.D.	β_{S_6}	$\bar{\beta}_{S_6}$	β_{S_7}	
1	CL-CEASD-2008-V-A	1,00	0	0	0	0	32	0	76	4	0,15	0,36	363,55
		1,20	0	0	0	0,00	36,80	0,00	76,00	4,00	0,15	0,36	411,55
2	CL-CEASD-2008-V-B	0,00	0	0	0	0	29	0	74	2	0,07	0,26	312,62
		0,00	0	0	0	1,20	31,20	0,00	74,00	2,00	0,07	0,26	364,62
3	CL-CECL-2011-M-A	7,00	0	0	0	4	41	0	81	5	0,16	0,36	563,63
		7,20	0	0	0	6,00	45,80	0,00	81,00	5,00	0,16	0,36	661,63
4	CL-CECL-2011-M-B	2,00	0	0	0	0	42	0	80	3	0,09	0,28	452,84
		1,20	0	0	0	2,80	43,60	0,00	80,00	3,00	0,09	0,28	538,84
5	CL-CECL-2011-N-A	1,00	0	0	0	0	20	0	67	8	0,27	0,51	285,12
		0,20	0	0	0	0,00	23,60	0,00	67,00	8,00	0,27	0,51	321,12
6	CL-CECL-2011-V-A	0,00	0	0	0	0	52	0	84	1	0,03	0,17	531,67
		0,20	0	0	0	0,80	57,00	0,00	84,00	1,00	0,03	0,17	601,67
7	CM-CECM-2011-M	4,00	0	0	2	7	94	0	130	7	0,14	0,34	1388,44
		145,00	0	0	2	17,00	101,80	0,00	130,00	7,00	0,14	0,34	1676,44
8	CM-CECM-2011-N	2,00	0	0	0	0	22	0	57	5	0,17	0,37	273,73
		43,00	0	0	0	0,40	24,00	0,00	57,00	5,00	0,17	0,37	303,73
9	CM-CECM-2011-V	3,00	0	0	0	0	32	0	84	5	0,15	0,35	373,54
		6,00	0	0	2	6,00	39,20	0,00	84,00	5,00	0,15	0,35	775,54
10	CM-CEDB-2010-N	0,00	0	0	0	0	11	0	32	0	0,00	0,00	110,00
		0,00	0	0	0	0,00	14,40	0,00	32,00	0,00	0,00	0,00	144,00
11	CM-CEUP-2008-V	5,00	0	0	0	0	66	0	95	1	0,03	0,17	671,67
		6,20	0	0	0	0,80	70,20	0,00	95,00	1,00	0,03	0,17	733,67
12	CM-CEUP-2011-M	4,00	0	0	0	0	68	0	98	2	0,05	0,22	702,23
		2,40	0	0	0	0,00	73,60	0,00	98,00	2,00	0,05	0,22	758,23
13	CM-CEUP-2011-N	0,00	0	0	0	0	7	0	24	0	0,00	0,00	70,00
		0,00	0	0	0	1,60	7,80	0,00	24,00	0,00	0,00	0,00	118,00
14	CM-CEUP-2011-V	5,00	0	0	0	0	43	0	98	3	0,09	0,28	462,84
		3,40	0	0	0	3,60	48,60	0,00	98,00	3,00	0,09	0,28	608,84
15	FA-EEF-2011-M	0,00	0	0	0	0	2	0	28	3	0,25	0,43	54,33
		0,00	0	0	0	0,00	2,00	0,00	28,00	3,00	0,25	0,43	54,33
16	JNS-CEDPII-2011-M	0,00	0	0	0	0	10	0	51	2	0,11	0,31	123,07
		0,00	0	0	0	0,00	11,60	0,00	51,00	2,00	0,11	0,31	139,07
17	JNS-CEDPII-2011-V	11,00	0	0	0	0	8	0	50	3	0,14	0,35	113,50
		2,40	0	0	0	2,00	11,60	0,00	50,00	3,00	0,14	0,35	239,50
18	JNS-CEJXXIII-2011-M	539,00	0	0	0	0	10	0	34	2	0,11	0,31	123,14
		107,80	0	0	0	0,00	12,40	0,00	34,00	2,00	0,11	0,31	147,14
19	JNS-CEJXXIII-2011-N	0,00	0	0	0	0	8	0	27	0	0,00	0,00	80,00
		0,00	0	0	0	0,00	9,00	0,00	27,00	0,00	0,00	0,00	90,00
20	JNS-CEJXXIII-2011-V	0,00	0	0	0	0	11	0	35	5	0,28	0,45	164,48
		0,00	0	0	0	0,00	13,40	0,00	35,00	5,00	0,28	0,45	188,48
21	MGA-CEDC-2011-M	2,00	0	0	0	0	61	0	112	1	0,03	0,16	621,60
		0,60	0	0	0	0,80	70,60	0,00	112,00	1,00	0,03	0,16	737,60
22	MGA-CEDC-2011-V	1,00	0	0	0	0	30	0	75	2	0,06	0,24	322,39
		1,20	0	0	0	0,40	34,20	0,00	75,00	2,00	0,06	0,24	374,39
23	MGA-CEGV-2011-M	51,00	0	0	2	6	145	0	189	7	0,11	0,32	1873,16
		54,80	0	0	1	15,40	151,40	0,00	189,00	7,00	0,11	0,32	2092,16
24	MGA-CEGV-2011-V	162,00	0	0	0	6	117	0	208	13	0,17	0,41	1454,12
		71,60	0	0	1	12,60	127,00	0,00	208,00	13,00	0,17	0,41	1779,12
25	MGA-CEJXXIII-2010-V	2,00	0	0	0	0	63	0	97	3	0,09	0,37	663,68
		2,40	0	0	0	1,80	64,80	0,00	97,00	3,00	0,09	0,37	746,68
26	MGA-CEVB-2011-M	0,00	0	0	0	0	21	0	62	2	0,10	0,29	232,94
		0,00	0	0	0	0,00	24,00	0,00	62,00	2,00	0,10	0,29	262,94
27	MGA-CEVB-2011-V	0,00	0	0	0	0	17	0	59	3	0,15	0,36	203,57
		0,00	0	0	0	0,00	22,20	0,00	59,00	3,00	0,15	0,36	255,57
28	NE-CESVP-2011-M-A	1,00	0	0	0	10	71	0	122	11	0,24	0,52	1075,23
		7,20	0	0	2	17,20	70,40	0,00	122,00	11,00	0,24	0,52	1469,23
29	NE-CESVP-2011-M-B	3,00	0	0	1	10	72	0	122	11	0,25	0,53	1185,28
		152,20	0	0	1	19,40	71,20	0,00	122,00	11,00	0,25	0,53	1452,28
30	NE-CESVP-2011-M-C	3,00	0	0	4	2	72	0	123	14	0,31	0,55	1315,51
		8,00	0	0	4	13,00	73,40	0,00	123,00	14,00	0,31	0,55	1584,51
31	NE-CESVP-2011-M-D	53,00	0	0	1	6	57	0	123	14	0,31	0,55	965,51
		112,80	0	0	1	11,40	62,20	0,00	123,00	14,00	0,31	0,55	1192,51
32	NE-CESVP-2011-V-A	45,00	0	0	4	12	55	0	113	12	0,27	0,45	1374,45
		27,40	0	0	4	15,60	59,80	0,00	113,00	12,00	0,27	0,45	1492,45
33	NE-CESVP-2011-V-B	8,00	0	0	1	6	35	0	110	10	0,23	0,47	704,74
		30,20	0	0	3	15,80	56,60	0,00	110,00	10,00	0,23	0,47	1325,74
34	NE-CESVP-2011-V-C	8,00	0	0	3	12	52	0	111	11	0,26	0,49	1234,87
		31,80	0	0	4	24,20	62,40	0,00	111,00	11,00	0,26	0,49	1723,87

Acknowledgments

This work was supported by CAPES, Brazil. The authors are grateful for their support and would like to thank the anonymous referees for their helpful comments.

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