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# A Hybrid Simulated Annealing- Genetic Algorithm for Course Time Tabling Problem

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***Abstract:** Course timetabling problem (CTP) consists on assigning a set of courses into a limited group of timeslots. Among the huge variety of algorithms proposed to solve it, Simulated Annealing (SA) is one with the best performance; even though not always find the optimal solution. Besides it is known that SA converges to a very good solution whether its parameters are correctly tuned. In this sense, how to improve SA performance is an open area; two general SA features require to be researched: 1) To improve its exploration capacity and 2) To develop confident tuning schemes. In this paper, a new hybrid algorithm named SA-GA is presented which it uses SA with Genetic Algorithms (GA). This hybridization uses a Markov tuning approach with a good exploration feature given by the genetic method in order to solve CTP. Also the mathematical CTP problem is presented and a several statistical significance testing method are applied.*

***Keywords:** (CTP), (SA), SA, CTP.*

## I. INTRODUCTION

The timetabling problem (TTP) consists on assigning a set of academic events (lectures, courses, exams) into a limited group of timeslots, subject to diverse constraints. The TTP is defined as **Error! Reference source not found.**:

*"The allocation, subject to constrains, of a set of given resources to events placed in time and space, in such a way to satisfy, as much as possible, a set of desirable objectives".*

Timetabling problems arise in many contexts including transportation timetabling 21, sports timetabling 17, employee timetabling 10 and educational timetabling 1, 4, 5. This kind of problems has been investigated during the last 40 years 2, 16, 22. Nevertheless, this research area continues to be attractive to the scientific community due to the evolving complexity of the problems, which in turn, makes necessary the development of new solution techniques 3, 18. Even et al. 6 demonstrated that timetabling problem is an *NP* - complete problem. The TTP is a search problem where the solution is any feasible timetable. However, in real situations, two feasible timetables may present differences (making one better than the other). Therefore, the objective is to find the optimum timetable. This last consideration makes the formulation of a timetabling problem as an optimization problem with an objective function to maximize (or minimize).16 From here that the timetabling problem is considered a *NP* – hard problem 12: as it is not possible to solve them by means of polynomial – time algorithms, heuristic methods need to be applied.

## II. UNIVERSITY TIMETABLING

The university timetabling problem deals with scheduling of semestral university courses to classrooms and time periods. The main difference between this problem and the school timetabling problems is that university courses have students in common instead of school timetabling which have different sets of students. If two courses have students in common then they cannot be scheduled at the same time. Also, the number of classrooms available and their size play a major role and they are not considered for the school timetabling problem, in which each class has its own classroom 16.

The information needed for the problem formulation is showed below:

- A set $q$ of courses $K_1,\ldots, K_q$ and for each $i$, the course $K_i$ has $k_i$ sessions.
- A set $r$ of academic programs $S_1,\ldots, S_r$, which are groups of courses with common students. That means that all courses that belong to $S_l$ must be scheduled for different time periods.
- $P$ time periods $1,\ldots, p$.
- The maximum amount of sessions that can be scheduled for period $k$, $l_k$.

The problem constraints states that:

- Each course is composed by the appropriate number of sessions, equation (3.8).
- The number of programmed sessions for each period of time must be at most the number of available classrooms, equation (3.9).
- The sessions in conflict must be programmed in different time periods, equation (3.10).

The mathematical formulation for the problem is:

Maximize:

$$\sum_{i=1}^{q}\sum_{k=1}^{p} C_{ik}\cdot y_{ik} \qquad (3.7)$$

Subject to:

$$\sum_{k=1}^{p} y_{ik} = k_i \quad (i=1,\ldots,q) \qquad (3.8)$$

$$\sum_{i=1}^{q} y_{ik} \le l_k \quad (k=1,\ldots,p) \qquad (3.9)$$

$$\sum_{i\in S_l} y_{ik} \le 1 \quad (l=1,\ldots,r;k=1,\ldots,p) \qquad (3.10)$$

Where:

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$y_{ik}$ = 1 if a session of course $K_i$ is programmed in period $k$ and
$y_{ik}$ = 0 in other case
$C_{ik}$ associated cost for programming a session of course $K_i$ for period $k$

## III. PATAT PROBLEM

PATAT problem consists of a set of events $E$ to be scheduled in 45 timeslots (5 days of 9 periods each), a set of rooms $R$ in which events take place, a set of students $S$ who attend the events and a set of features $F$ satisfied by rooms and required by events. Each student attends a number of events and each room has limited capacity. A feasible timetable is one in which all events have been assigned a timeslot and a room, so the following hard constraints are satisfied 11:

- No student attends more than one event at the same time.
- The room is big enough for all the attending students and satisfies all the features required by the event.
- Only one event is in each room at any timeslot.
  In addition, a feasible timetable is penalized equally for the occurrence of the following soft constraints violations:
- A student has a class in the last period of the day.
- A student has more than two consecutive classes.
- A student has a single class on a day.

## IV. HYBRID ALGORITHM

Various methods of hybridization have been proposed for improving the GAs behavior 7. In literature, exists many articles that discuss the hybrid genetic approach (12, 13, 19, 20) and show that it is a good option to solve hard optimization problems.
During the last 20 years, several algorithms have been proposed to a great number of combinatorial optimization problems, like the travelling salesman problem (TSP), vehicle scheduling, jop shops, etc., this algorithms have been denominated like meta-heuristics which, unlike specific heuristic techniques (applicable only to the problem that is desired to solve), have the characteristic of being robust techniques able to be adapted to solve the different problems mentioned previously. This term was introduced by Glover in 1986 and are frequently called modern heuristics thanks to Reeves in 1993. The term meta-heuristics was formally established by Osman and Laporte in 1996 as an iterative process guiding subordinated heuristics by combining different intelligent concepts in order to explore the search space, and learning strategies to structure information and then to find efficient solutions, near to the optimum.
The present work has as main objective the development and application of a hybrid technique that combines two meta-heuristics having demonstrated to have good results in the solution of combinatorial problems; as Genetic Algorithms (GA) and Simulated Annealing (SA) applied to solve the ELDSP problem with a finite horizon in a Flexible Flow Shop.
Figure 1 shows the proposed hybrid algorithm. The algorithm begins creating an initial population. As is recommended to employ small populations, populations of size ten (ten individuals) are considered. Then individuals are selected according to their level of fitness using universal stochastic sampling. The selected individuals enter one by one, into a Metropolis cycle (outside cycle of temperature and an inside cycle). After that, crossover and mutation operators are applied to the new population to generate the next generation.
This process is repeated until a stoppage criterion is satisfied (in our case, until the process reaches ten generations).

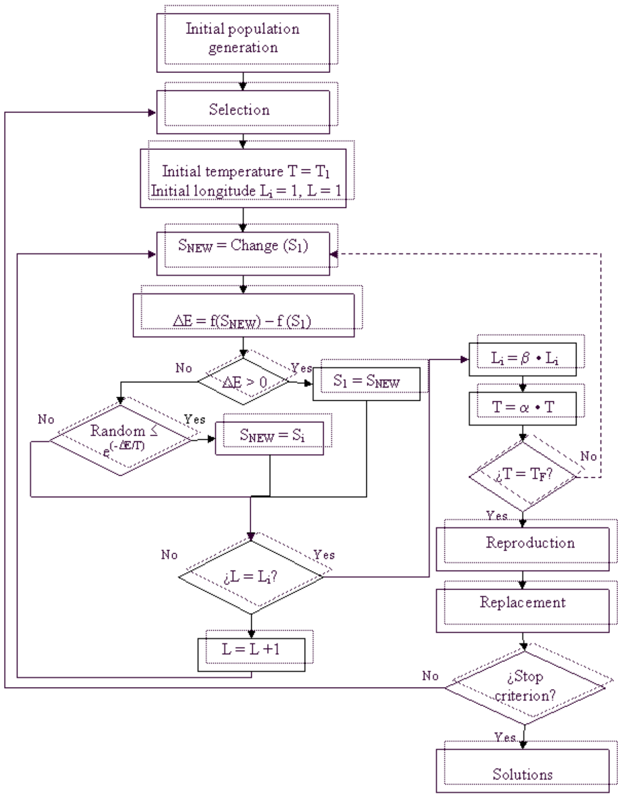


**Fig. 1. Hybrid Algorithm**

## V. CHROMSOME

The proposed chromosome for PATAT problem uses an integer representation, in which every allele represents an event scheduled in a specific room, at a specific timeslot. The chromosome's length is defined by the quantity of timeslots multiplied by the quantity of rooms (see figure 2).

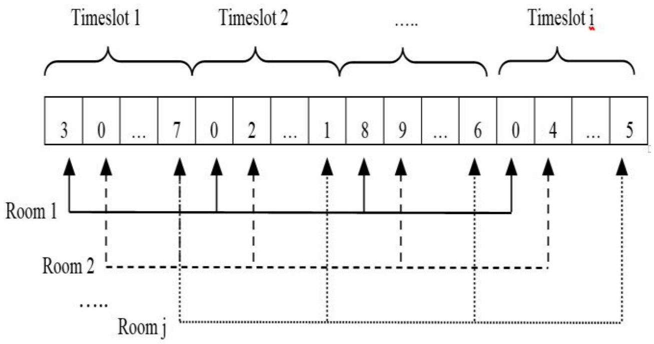


**Fig. 2. Chromosome's representation**

## VI. FITNESS FUNCTION

The fitness function is a weighted sum of the number of hard and soft constraints not satisfied.

Fitness function = $\gamma \cdot HCV + (1-\gamma) \cdot SCV$ **(1)**

Where HCV and SCV represent the number of hard and soft constraint violations. The $\gamma$ value should be big enough to penalize a hard constraint violation as if all soft constraints were not satisfied. 8. It is considered a $\gamma$ value equals to 0.9998 for small instances and 0.9999 for medium instances.


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## VII. NEIGHBORHOOD STRUCTURE

The neighborhood structure employed in a Metropolis cycle is the same utilized by 9, and it consists on randomly select two chromosome's locus (two timeslots and two rooms) and exchange their events (as shown in figure 3).

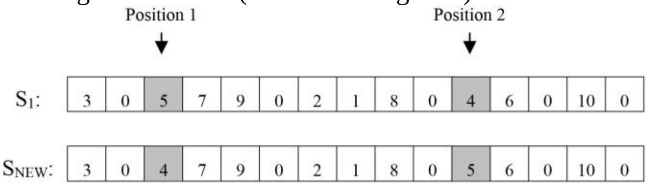


Fig. 3. Neighborhood structure for a Metropolis cycle

## VIII. COOLING SCHEME PARAMETERS

The method proposed by Sanvicente and Frausto [16] is adopted in order to set the cooling scheme parameters. This method states that initial and final temperatures should be a function of maximum and minimum deteriorations of the cost function produced through the neighborhood structure. This allows to considerably reduce the number of trials executed in the search for the best algorithm's parameters 9.
The cooling scheme utilized is geometric:

$$T_{i+1} = \alpha \cdot T_i \qquad \alpha < 1 \tag{2}$$

As a result, the temperature is geometrically reduced, iteration after iteration, as indicated by equation (2) which considers an α value of 0.90.
In order to set the number of iterations required to be executed at every temperature (Markov chain); it is necessary to calculate the value of $n$ with the initial and final temperature values obtained through the neighborhood structure employed.

$$n = \frac{\ln T_F - \ln T_1}{\ln \alpha} \tag{3}$$

It is necessary to determine the value of $L_1$ and $L_{max}$ to obtain the factor β which increments the Markov chain's length. When $T_i = T_1$, a single iteration is enough, this means that the Markov chain's length at the initial temperature is $L_1 = 1$. In order to calculate $L_{max}$, it is required to assess the desirable exploration level and the neighborhood size. It is desirable a neighborhood exploration level of 95% or $C$ = 3 15, and the size of the neighborhood may be calculated using equation 4, which multiplies the number of events and the number of events minus one.

$$L_{max} = C \cdot \left|V_{S_i}\right| = 3 \cdot \text{número de eventos} \cdot (\text{número de eventos - 1}) \tag{4}$$

It is possible to calculate β value by substituting the obtained results from equations (3) and (4), into the following equation:

$$\beta = \exp \frac{\ln L_{max} - \ln L_1}{n} \tag{5}$$

The values obtained through setting the parameters are summarized in the next table:

**Table 1. Cooling scheme parameters**

| Parameter | Small | Medium |
|---|---|---|
| Initial temperature ($T_1$) | 1,950 | 4,874 |
| Final temperature ($T_F$) | 0.01 | 0.01 |
| $L_1$ | 1 | 1 |
| $L_{max}$ | 29,700 | 478,800 |
| β | 1.093 | 1.110 |

## IX. GENETIC OPERATORS

The crossover operator follows a set of steps (figure 4):

1) Start with two original individuals ($P_1$ and $P_2$) and generate two more ($O_1$ and $O_2$).
2) Randomly select a crossover point (the same in both parents).
3) Copy the first part of $P_1$ into $O_1$.
4) Chose the alleles from parent $P_2$ not present in the first part of $P_1$, in order to fill the last part of $O_1$.
5) Copy the first part of $P_2$ and the alleles from individual $P_1$ (missing in the first part of $P_2$), in order to generate $O_2$.

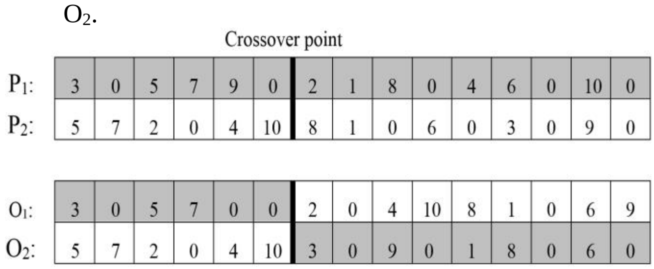


**Fig. 4. Single point crossover operator**

The mutation operator requires the random selection of two points and a length (within the individual). The section of random length (starting at the first point) is exchanged with the other section of the same length (starting at the second point). See figure 5

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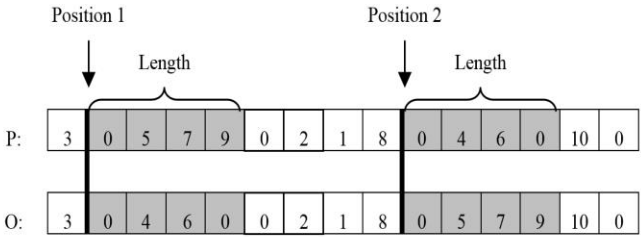


**Fig. 5. Mutation operator**

The crossover and mutation probabilities were evaluated experimentally. Different probability values were tested (i.e. 0.001, 0.005, 0.01, 0.05, 0.1 and 0.15). The value of 0.15 provided the best results (in terms of fitness function) for the generational mean and the best of the generation. For this reason, this value was employed in the present work.

## X. EXPERIMENTAL RESULTS AND CONCLUSIONS

The genetic algorithm, simulated annealing, and tuned simulated annealing were launched 100 runs or experiments, while the hybrid algorithm was executed 15 times.


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The genetic and hybrid algorithm considered 200 and 10 generations respectively. The initial and final temperatures, and β value for tuned simulated annealing and hybrid algorithm are shown in table 1. The initial and final temperatures for simulated annealing are the ones proposed by 9, which were obtained using a manual parameter setting. The techniques mentioned were applied to four PATAT instances. See figures 6, 7 and 8.

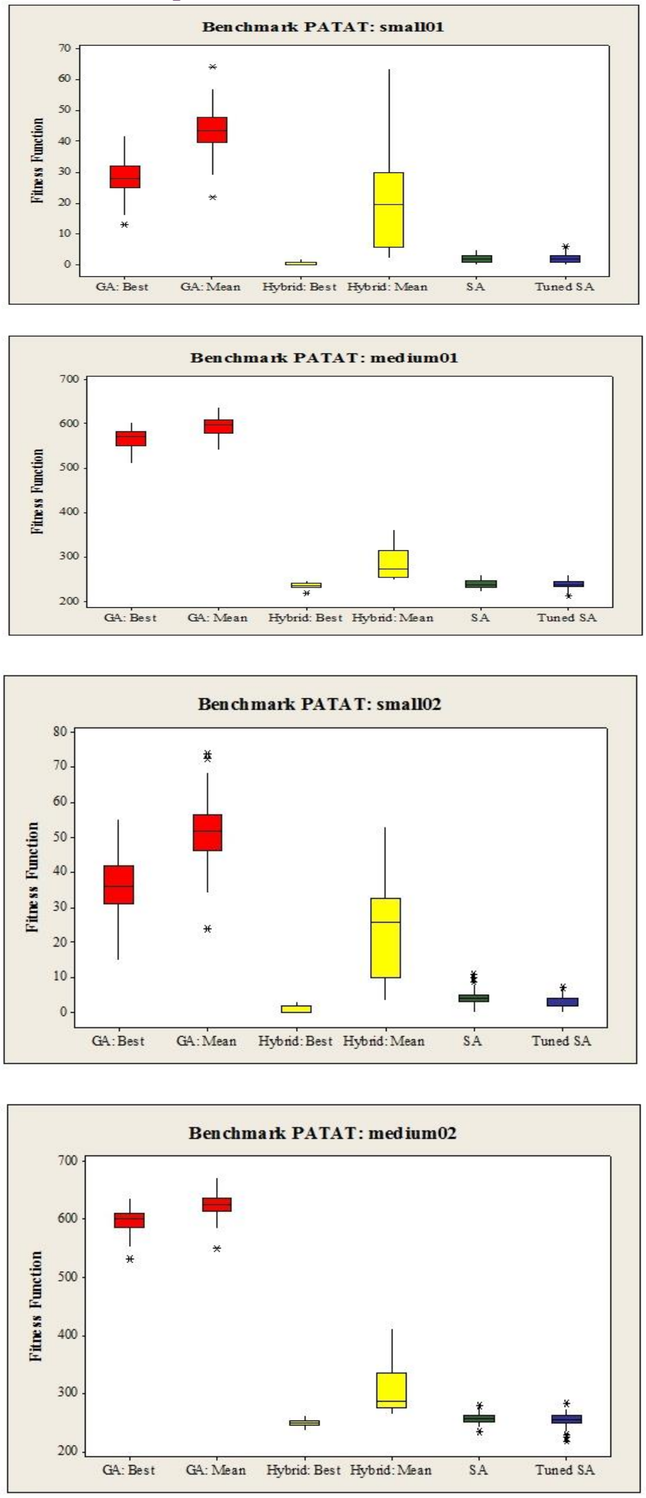


**Fig. 6. Fitness function for PATAT instances using GA, SA and hybrid GA – SA**

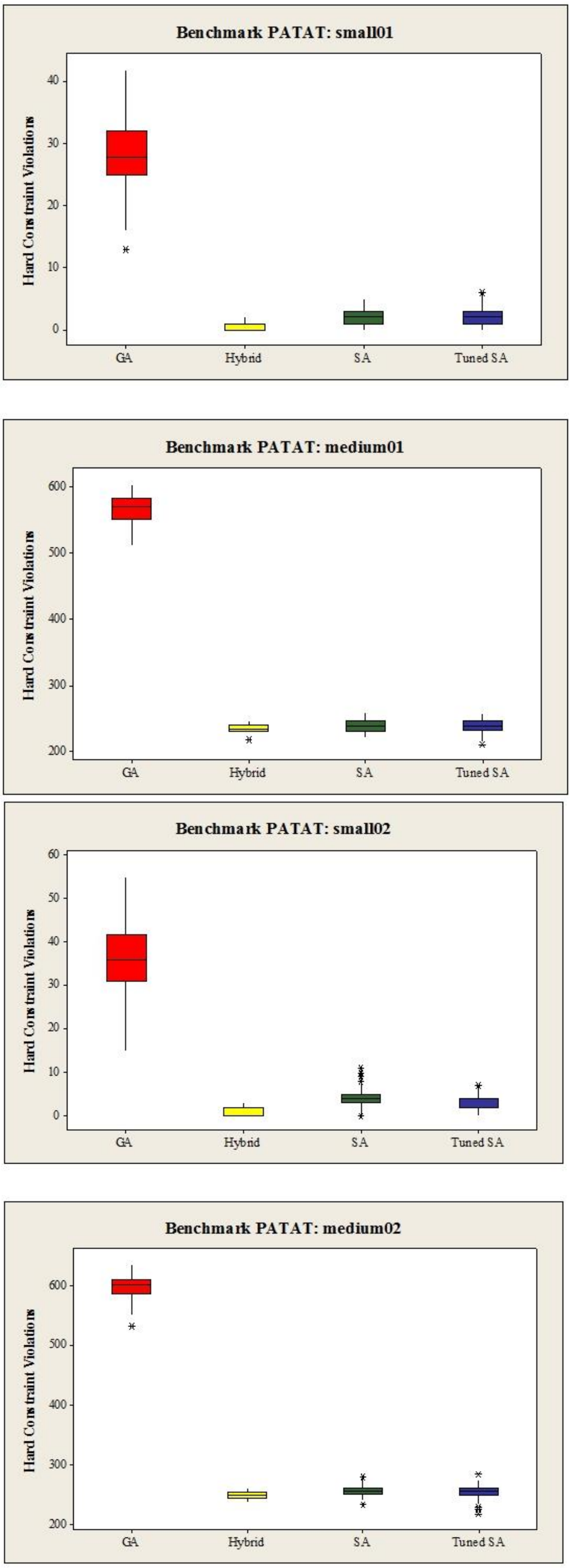


**Fig. 7. Hard constraint violations for PATAT instances using GA, SA and hybrid GA – SA**

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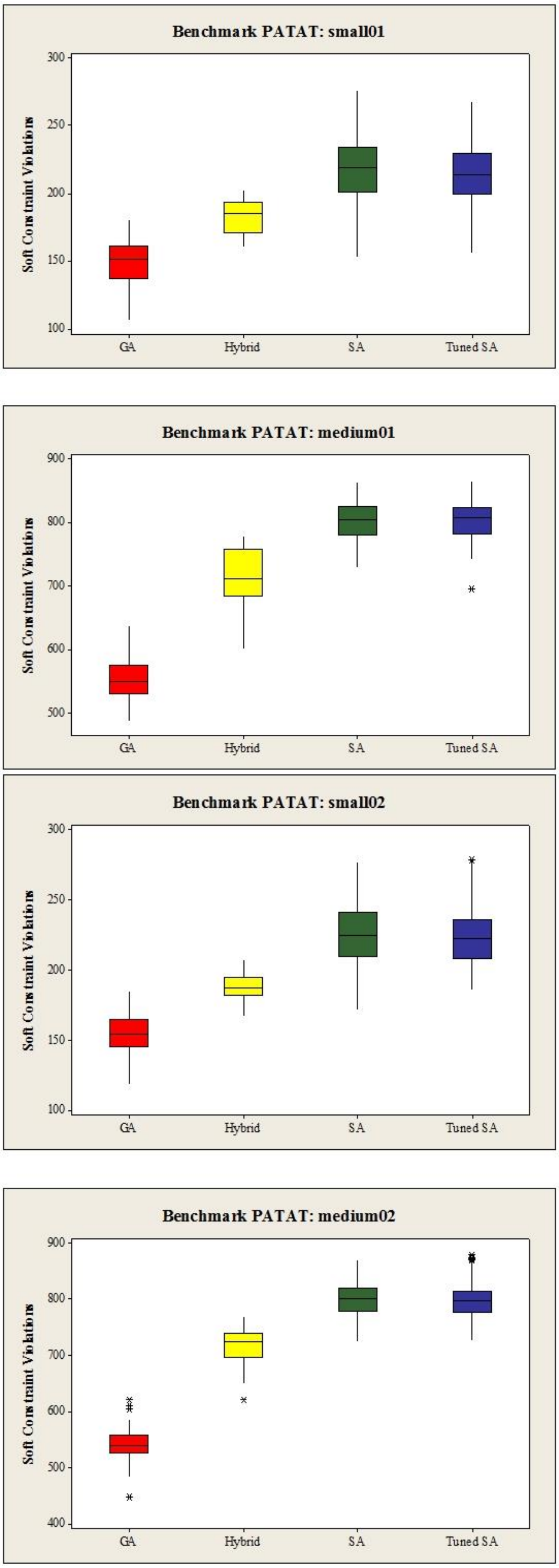


**Fig. 8. Soft constraint violations for PATAT instances using GA, SA and hybrid GA – SA**

In order to determine if there is a significant difference among the results offered by the different techniques, a variance analysis and a Fisher paired comparison were performed. The conclusions obtained are summarized as follows:

For all the PATAT instances, there is statistical evidence to conclude that the performance of the genetic algorithm (better value) is inferior to the performance of simulated annealing, tuned simulated annealing and hybrid algorithm. For PATAT instances small01 and medium01, there are no significant statistical difference between the performances of simulated annealing, tuned simulated annealing and hybrid algorithms. On the other hand, for the PATAT instance small02, the performance of simulated annealing is inferior to that of tuned simulated annealing and hybrid algorithm, and there is no significant statistical difference between the performance of tuned simulated annealing and hybrid algorithm. For PATAT instance medium02, the performance of simulated annealing is inferior to that of the hybrid algorithm. Finally, there is no significant statistical difference between the performance of tuned simulated annealing regarding to the performance of the simulated annealing and the hybrid algorithm.

For all the PATAT instances, there is statistical evidence to conclude that the performance of the genetic algorithm (better value) is inferior to the performance of simulated annealing, tuned simulated annealing and hybrid algorithm. For PATAT instances small01 and medium01, there are no significant statistical difference between the performances of simulated annealing, tuned simulated annealing and hybrid algorithms. On the other hand, for the PATAT instance small02, the performance of simulated annealing is inferior to that of tuned simulated annealing and hybrid algorithm, and there is no significant statistical difference between the performance of tuned simulated annealing and hybrid algorithm. For PATAT instance medium02, the performance of simulated annealing is inferior to that of the hybrid algorithm. Finally, there is no significant statistical difference between the performance of tuned simulated annealing regarding to the performance of the simulated annealing and the hybrid algorithm.

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