CONSTRAINT BASED SCHEDULING IN A GENETIC ALGORITHM FOR THE SINGLE MACHINE SCHEDULING PROBLEM WITH SEQUENCE-DEPENDENT SETUP TIMES

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Abstract: This paper presents a hybrid approach based on the integration between Genetic Algorithm (GA) and Constraint Based Scheduling (CBS) approaches for solving a scheduling problem. The main contributions are the integration of the CBS approach in the reproduction and the intensification processes of a GA autonomously. The proposed methodology is applied to a single machine scheduling problem with sequence-dependent setup times for the objective of minimizing the total tardiness. A sensitivity analysis of the hybrid methodology is carried out to compare the performance of the GA and the integrated GA-CBS approaches on different benchmarks from the literature.

1 INTRODUCTION

Several researches on scheduling problems have been done under the assumption that setup times are independent of job sequence. However, in certain contexts, such as the pharmaceutical industry, metallurgical production, electronics and automotive manufacturing, there are frequently setup times on equipment between two different activities. Production of good schedules often relies on management of these setup times (Allahverdi et al., 2008). This present paper considers the single machine scheduling problem with sequence dependent setup times with the objective to minimize total tardiness of the jobs (SMSDST). This problem, noted as $1|s_{ij}|\Sigma T_j$ in accordance with the notation of Graham, Lawler, Linstra and Rinooy Kan (1979) , is an NP-hard problem (Du and Leung, 1990).

The $1|s_{ij}|\Sigma T_j$ may be defined as a set of n jobs available for processing at time zero on a continuously available machine. Each job j has a processing time p_j, a due date d_j, and a setup time s_{ij} which is incurred when job j immediately follows job i. It is assumed that all the processing times, due dates and setup times are non-negative integers. A sequence of the jobs $S = [q_0, q_1, ..., q_{n-1}, q_n]$ is considered where q_j is the subscript of the j^{th} job in the sequence. The due date and the processing time of the j^{th} job in sequence are denoted as d_{q_j} and p_{q_j}, respectively. Thus, the completion time of the j^{th} job in sequence will be expressed as $C_{q_j} = \sum_{k=1}^{j}(s_{q_{k-1}q_k} + p_{q_k})$ while the tardiness of the j^{th} job in sequence will be expressed as $T_{q_j} = max(0, C_{q_j} - d_{q_j})$. The objective of the scheduling problem studied is to minimize the total tardiness of all the jobs which will be expressed as $\sum_{j=1}^{n} T_{q_j}$.

In this paper, we present a hybrid approach based on Genetic Algorithm (GA) and Constraint Based Scheduling (CBS) to solve this problem. The CBS approach has become a widely used form for modeling and solving scheduling problems using the constraint programming approach. The hybridization of the CBS approach with the GA is done at two levels. Indeed, the CBS is used in the reproduction and intensification processes of GA separately and this represents the paper's main contributions. In fact, the CBS approach is integrated in a crossover operator and in the intensification search space process using additional constraints for both of them. Computational testing is performed on a set of test problems available from literature. We report on our experimental results and conclude with some remarks and future research directions. As a constraint programming environment, we use the ILOG IBM CP environment using ILOG Solver and ILOG Scheduler via the C++ APIs (ILOG, 2003b; ILOG, 2003a). The use of this kind of platforms has been encouraged by the steady

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improvement of general purpose solvers over the past decade. Such solvers have become significantly more effective and robust (Yunes et al., 2010). Also, the C++ APIs allow users to develop their own strategies for a particular problem. Moreover, this interface enables a better interaction with other applications than the OPL interface (ILOG, 2003b).

2 LITERATURE REVIEW

Considering the objective of minimizing the makespan in the basic single machine problem without setup times, any permutation of jobs gives the same makespan. Nevertheless, the addition of the sequence dependent setup times considerably complicates the problem (Allahverdi et al., 2008). This problem with the objective of minimizing the makespan is equivalent to the Travelling Salesman Problem (TSP), which is NP-hard. In addition, this problem is even more difficult when total tardiness is the performance measure and there has been relatively little research reported on it. Furthermore, in presence of sequence dependent setup times, most of the research has focused on either minimizing the sum of setup times or minimizing the sum of job completion times (Allahverdi et al., 2008).

Different approaches have been proposed by a number of researchers to solve the problem. Rubin and Ragatz (1995) proposed a Branch and Bound approach, which quickly showed its limitations. It could solve to the optimality only small instances of benchmark files of 15, 25, 35 and 45 jobs proposed by these authors. Bigras, Gamache and Savard (2008) solved to the optimum all instances proposed by Rubin and Ragatz (1995) using a Branch and Bound approach with linear programming relaxation bounds. They also demonstrated and used the problem's similarity with the time-dependent traveling salesman problem. Such Branch and Bound approach solved some of these instances by more than 7 days. Because this problem is NP-hard, many researchers used a wide variety of metaheuristics to solve this problem such as genetic algorithm (Franca et al., 2001; Sioud et al., 2009), memetic algorithm (Armentano and Mazzini, 2000; Franca et al., 2001; Rubin and Ragatz, 1995), simulated annealing (Tan and Narasimhan, 1997), GRASP (Gupta and Smith, 2006), ant colonies optimization (Gagné et al., 2002; Liao and Juan, 2007) and Tabu/VNS (Gagné et al., 2005). Heuristics such as Random Start Pairwise Interchange (RSPI) (Rubin and Ragatz, 1995) and Apparent Tardiness Cost with Setups (ATCS) (Lee et al., 1997) have also been proposed for solving this problem. For their part, Spina, Galantucci and Dassisti (2003) introduce a hybrid approach using constraint programming and genetic algorithm sequentially. In this latter case, the authors have considered a real world problem with a maximum of ten jobs.

3 THE HYBRID GENETIC ALGORITHM

In their respective works, Rubin and Ragatz (1995) and Sioud, Gravel and Gagné (2009) have shown the importance of relative and absolute order positions for the $1|s_{ij}|\Sigma T_j$ problem. Thereby, all the used crossover operators into the genetic algorithms from literature maintain the absolute position, or the relative position or both. Indeed, Rubin and Ragatz (1995) used a specific operator which alters the conservation of the absolute and the relative order by generating random sub-sequences of jobs separately for each offspring. Armentano and Mazzini (2000) modified the ERX crossover while Franca, Mendes and Moscato (2001) developed a genetic and a memetic algorithms using the OX crossover. Sioud et al. (2009) proposed RMPX, a new crossover operator which takes greater account of the relative and absolute position job and gives better results than other crossovers.

To reach good results, the presented hybrid genetic algorithm must ensure the preservation of both the relative and the absolute order positions while maintaining diversification during its evolving. In this context, the genetic algorithm and the two hybridization approaches will take this into consideration.

3.1 Genetic Algorithm

Genetic algorithms are methods based upon biological mechanisms such as the genetic inheritance laws of Mendel and the natural selection concept of Charles Darwin, where the best adapted species survive. The basic concepts of GA have been described by the investigation carried out by Holland (1992) who explained how to add intelligence into a program computing with the crossover exchange of genetic material and transfer as a source of genetic diversity. In a GA, a population of individuals or chromosomes incurs a sequence of transformations by means of genetic operators to form a new population. Two main operators are used for this purpose : crossover and mutation. Crossover creates new individuals by combining parts of two individuals and mutation creates new individuals by a small change in a single individual.

Based on the GA proposed by Sioud et al. (2009), we redefine a simple genetic algorithm. A solution is coded as a permutation of the considered jobs. The population size is set to *n* to fit with the considered instance size. The initial population is randomly generated for 60% and also for 20% using a pseudo-random heuristic which favors setup times and promotes a relative order for the jobs. The last 20% is generated using a pseudo-random heuristic which depends on due dates and promotes an absolute order for the jobs. A binary tournament selects the chromosomes for the crossover. The proposed GA uses the OX crossover (Michalewicz, 1996) to generate 30% of offspring and the RMPX crossover (Sioud et al., 2009) to generate the rest of the children population. Both of the OX and RMPX crossover maintain both of the relative and the absolute order positions, but the RMPX crossover seems to give better results. The RMPX crossover can be described in the following steps : (i) two parents P1 and P2 are considered and two distinct crossover points *C1* and *C2* are selected randomly, as shown in Figure 1; (ii) an insertion point p_i is then randomly chosen in the offspring E as p_i = *random (n – (C2 – C1))*; (iii) the part [*C1*, *C2*] of P1, shaded in Figure 1, is inserted in the offspring E from p_i. The insertion is to be done from the position 2 showing in Figure 1; and (iv) the rest of the offspring E is completed from P2 in order of appearance since its first position.

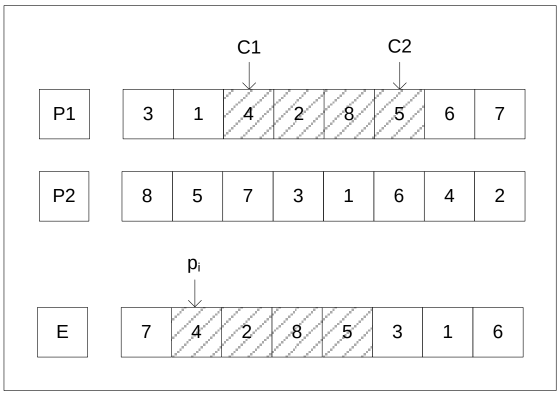


Figure 1: Illustration of RMPX.

The crossover probability *pc* is set to 0.8, i.e. therefore *n*0.8* offspring are generated at each generation in which a mutation is applied with a probability *pm* equal to 0.3. The mutation consists of exchanging the position of two distinct jobs which are randomly chosen. The replacement is elitist and the duplicates individuals in the population were replaced by chromosomes which are generated by one of the pseudo-random heuristics used in the initialization phase. The stop criterion is set to 3000 generations.

3.2 Constraint based Scheduling

Constraint solving methods such as domain reduction and constraint propagation have proved to be well suited for a wide range of industrial applications (Fromherz, 1999). These methods are increasingly combined with classical solving techniques from operations research, such as linear, integer, and mixed integer programming (Talbi, 2002), to yield powerful tools for constraint-based scheduling by adopting them. The most significant advantage of using such CBS is to separate the model from the algorithms which solve the scheduling problem. This makes it possible to change the model without changing the algorithm used and vice versa.

In the recent years, the CBS has become a widely used form for modeling and solving scheduling problems using the constraint programming approach (Baptiste et al., 2001; Allahverdi et al., 2008). A scheduling problem is the process of allocating tasks to resources over time with the goal of optimizing one or more objectives (Pinedo, 2002). A scheduling problem can be efficiently encoded like a constraint satisfaction problem (CSP).

The activities, the resources and the constraints, which can be temporal or resource related, are the basis for modeling a scheduling problem in a CBS problem. Based on representations and techniques of constraint programming, various types of variables and constraints have been developed specifically for scheduling problems. Indeed, the domain variables may include intervals domains where each value represents an interval (processing or early start time for example) and variable resources for many classes of resources. Similarly, various research techniques and constraints propagation have been adapted for this kind of problem.

In Constraint Based Scheduling, the single machine problem with setup dependent times can be efficiently encoded in terms of variables and constraints in the following way. Let *M* be the single resource. We associate an activity A_j for each job *j*. For each activity A_j four variables are introduced, *start*(A_j), *end*(A_j), *proc*(A_j) and *dep*(A_j). They represent the start time, the end time, the processing time and the departure time of the activity A_j, respectively. The departure time represents the needed setup time of an activity when the latter starts the schedule.

A setup time s_{ij} is introduced and it is incurred when job *j* immediately follows job *i*. In our case, the setup times are activity related and not resource-related. For this purpose, we assign a type to each activity and a lattice to the unary machine. Then, when we calculate the objective function, it is possible to

```
L1    Modeling SMSDST :
L2
L3      procedure CreateMachine (SetupMatrix)
L4          Create the setup matrix parameter
L5          Create the single machine and associate the setup matrix parameter
L6      end CreateMachine()
L7
L8      procedure CreateJob (ProcessingTimes, StartingTimes, type)
L9          Create a job with a type and processing time
L10          Set a starting time for the created job
L11      end CreateJob()
L12
L13     procedure ModelSMSDST(ProcessingTimes, StartingTimes, DueDates SetupMatrix)
L14         CreateMachine(SetupMatrix)
L15         Define an array for the jobs completion time C
L16         Define a variable for the total tardiness Tard
L17         for each i in NB_JOBS do
L18             job     CreateJob (ProcessingTimes, StartingTimes, i)
L19             C[i]     max(0, job.end - DueDates[i])
L20         end for
L21         Tard     Sum(C)
L22         Minimize (Tard)
L23     end ModelSMSDST
```

Figure 2: C++ API model for the $1|s_{ij}|\Sigma T_j$ problem.

associate the transition times between two distinct types of activities. The tardiness criterion is represented by an additional variable *Tard*. Its value is determined by $Tard = \sum_{A_j=1}^{n} max(end(A_j) - d_{A_j}, 0)$.

Figure 2 presents the pseudo-code for the $1|s_{ij}|\Sigma T_j$ problem modeling with the C++ API of ILOG Scheduler 6.0. The main procedure ModelSMSDST calls the two procedures CreateMachine and CreateJob. CreateMachine procedure (lines 3 to 6) uses the class *IloUnaryResource*. This allows handling unary resources, that is to say, a resource whose capacity is equal to one. This resource cannot therefore handle more than one job at a time. The use of the setup times in CBS and also with ILOG Scheduler 6.0 (ILOG, 2003a) indicates that they are resource-related and not activity-related such as is the case in our problem. It is possible to overcome this problem by associating a type for each activity and creating setup times associated with these types. For this purpose, we use the class *IloTransitionParam* which is managing and setting setup times. The setup matrix is then associated to this class which will be related to the unary machine (line 5). Thus, when we calculate the objective function, it is possible to associate the setup times between two distinct types of activities. To model the total tardiness, we must first define a variable *Tard* (line 16). Then we define an array C containing the completion times C_i of the different activities times A_i during the research phase (line 15). When we create the activities in the model, we add a constraint that combines the activities A_i to the corresponding times C_i (line 19). After that, we add a constraint which combines the variable *Tard* with the sum of the C_i in the table C (line 21). Finally, we add a constraint that minimizes the variable *Tard* (line 22). Thus, we obtain the objective function which will be added to the model.

ILOG Solver (2003) provides several predefined search algorithms named as *goals* and activity selectors. We used the *IloSetTimesForward* algorithm with the *IloSelFirstActMinEndMin* activity selector. The *IloSetTimesForward* algorithm schedules activities on a single machine forward initializing the start time of the unscheduled activities. The activity selector defines the heuristic scheduling variables representing start times, which chooses the next activity to schedule. The *IloSelFirstActMinEndMin* tries first the activity with the smallest start time and in case of equality the activity with the smallest end time. For his part, ILOG Scheduler (2003) provides four strategies to explore the search tree : the default *Depth-First Search* (DFS), the *Slice-Based Search* (SBS) (Beck and Perron, 2000), Interleaved Depth-First Search (IDFS) (Meseguer, 1997) and the *Depth-Bounded Discrepancy Search* (DDS) (Walsh, 1997) which is used in this work.

3.3 Hybrid Approach

The hybridization of an exact method such as the CBS and a metaheuristic such as the GA can be carried out in several ways. Talbi (2002) presents a taxonomy dealing with the hybrid metaheuristics in general. Puchinger and Raidl (2005) and Jourdan, Basseur and Talbi (2009) present a taxonomy for the exact methods and metaheuristics hybridizing. In this paper we present two different approaches of hybridization. The first approach is to integrate the CBS in the GA reproduction phase and more precisely in a crossover operator, while the second approach is to use CBS as an intensification process in the GA.

When we handle a basic single machine model, there is no precedence constraint between activities as is the case in a flow-shop or job-shop where adding constraints improves the CBS approach. The main idea of integrating the CBS in a crossover is to provide to this latter precedence constraints between activities when generating offspring. In this work, we consider only the direct constraints during the crossover. Therefore, the conceived crossover promotes the relative order positions such as the PPX crossover (Bierwirth et al., 1996). The proposed crossover operator is designated *Precedence Constraint Crossover (PCX)* and can be described in the two following steps : *(i)* two parents P1 and P2 are considered and the precedence constraints between activities concurrently in both parents are kept, as shown in Figure 3; and *(ii)* the CBS approach tries to solve the problem while adding the precedence constraints built in the previous step and an upper bound consisting of the objective function value of the best parent. The upper bound is added to discard faster bad solutions when branching during the solver process. As a reminder, the ILOG Solver uses a Branch and Bound approach to solve a problem (ILOG, 2003b). In the case of Figure 3, the two precedence constraints (4 before 6) and (7 before 5) are added to the model and will be propagated. Thus, these two constraints, preserve the relative positions of the pairs of activities (4,6) and (7,5). E1, E2 and E3 represent three potential offspring where the two precedence constraints (4 before 6) and (7 before 5) are preserved. Then, if the two selected parents are "good" solutions, preserving the relative order could in turn generate also "good" solutions. Finally, if no solution is found by the PCX crossover, the offspring is generated by one of the pseudo-random heuristics used in the initialization phase. The PCX crossover will be done under probability p_{PCX}.

Integrating an intensification process in a genetic algorithm has been applied successfully in several fields. The incorporation of heuristics and/or other methods, i.e. an exact method such as the CBS approach, into a genetic algorithm can be done in the initialization process to generate well-adapted initial population and/or in the reproduction process to improve the offspring quality fitness. Following this latter reasoning, the strategy proposed in this paper is based on the intensification in specific space search areas. However, we can find in literature only few papers dealing with such hybridization (Puchinger and Raidl, 2005; Talbi, 2009).

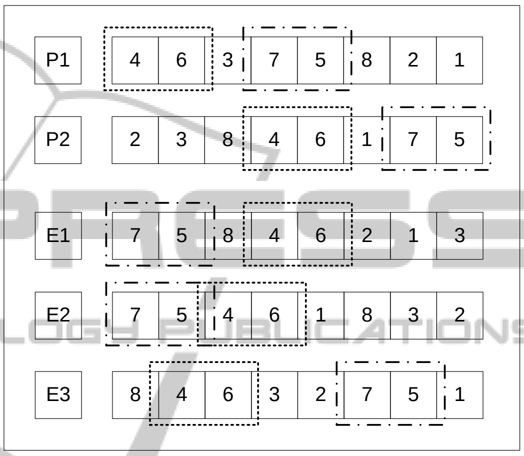
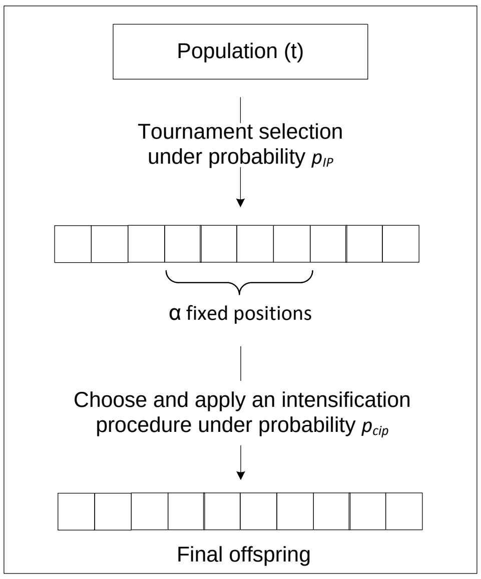


Figure 3: Illustration of PCX.

In the same vein of the PCX conservation precedence constraints, an intensification process is applied by giving a generated offspring to the CBS approach and fixing a block of α positions. Thus, the absolute order position will be preserved for these fixed positions while the relative order position will be preserved for the other activities. Indeed, the activities on the left of the fixed block will be scheduled before this late block, while the activities on the right will be scheduled after this block. The fixed block size should be neither too large nor too small : if its size is too large, the CBS approach will have no effect and if its size is too small the CBS approach will consume more time to find a better solution. Thereby, at each time this intensification is done, α continuous positions are fixed with $0.2*n \prec \alpha \prec 0.4*n$. We use to this end two different procedures based on the CBS approach. The first one, noted as IP_{TARD}, selects a generated offspring and tries to solve the problem using the CBS approach which minimizes the total tardiness described above while adding an upper bound consisting of the objective function value of this offspring. So as a result, the CBS approach may return a better solution when scheduling separately the activities on the left and the right of the fixed block activities.

Using the similarity of the studied problem with the time-dependent traveling salesman problem (Bigras et al., 2008), the second intensification procedure, noted as IP$_{TSP}$, works like IP$_{TARD}$ but in this case the CBS approach minimizes the makespan. The makespan optimization aims to minimize the setup times and then, in some specific configurations, will give promising solutions under total tardiness optimization otherwise explore a different areas search space. The makespan criterion is represented by an additional variable Makespan. Its value is determined by $Makespan = \sum_{A_j=1}^{n} max(end(A_j))$. The model minimizing the makespan is similar to that in Figure 2. Indeed, we just delete the declaration of the array C at line 15 and define an activity Makespan with time processing equal to 0 at line 16. Then, a constraint stating that all jobs must be completed before the Maskespan start time is added in the for loop. Finally, lines 19 and 21 are removed and line 22 minimizes in this case the Makespan end time.

Thereby, an offspring is selected with a tournament under probability p_{IP} and then, one of the two intensification procedures IP$_{TARD}$ and IP$_{TSP}$ is chosen under probability p_{cip} to be applied on this offspring. Figure 4 illustrates the intensification process based on the CBS approach. At each generation, an offspring is selected under probability p_{IP} with tournament selection. After fixing α positions and choosing an intensification procedure, IP$_{TARD}$ or IP$_{TSP}$ under probability p_{cip} , the solver tries to find a solution. If no solution is found the offspring is unchanged.



Population (t)
Tournament selection under probability p_{IP}
α fixed positions
Choose and apply an intensification procedure under probability p_{cip}
Final offspring

Figure 4: The intensification process.

4 COMPUTATIONAL RESULTS AND DISCUSSION

The benchmark problem set consists of eight instances, each with a number of jobs of 15, 25, 35 and 45 jobs, and it is taken from the work of Ragatz (1993). These instances are available on the Internet at https://www.msu.edu/˜rubin/files/c&ordata.zip. The job processing times are normally distributed with a mean of 100 time units and the setup times are also uniformly distributed with a mean of 9.5 time units. Each instance has three factors which have both high and low levels. These factors are due date range, processing time variance and tardiness factor. The tardiness factor determines the expected proportion of jobs that will be tardy in a random sequence. All the experiments were run on an Itanium with a 1.4 GHz processor and 4 GB RAM. Each instance was executed 5 times and the results presented represent the average deviation with the optimal results of Bigras et al. (2008) . All the algorithms are coded in C++ language under the ILOG IBM CP constraint environment using ILOG Solver and Scheduler via the C++ API (ILOG, 2003b; ILOG, 2003a).

Table 1 compares the results of different approaches. In this table, PRB denotes the instance names and OPT the optimal solution found by the B&B of Bigras et al. (2008). These authors have not given information about the execution time of their approach. They only said that some instances have been resolved after more than seven days. The GA column shows the results average deviation to the optimal solution of the genetic algorithm described in the section 3.1 which gives the best results among all genetic algorithms in the literature without an intensification process (Sioud et al., 2009). The GA average CPU time is equal to 13.4 seconds for the 32 instances. The GA generally obtained fairly good results only for the instances 601, 605, 701 and 705. These instances are low due date range and large tardiness factor. Thus, for this kind of instances, ”good” solutions may not generate ”good” offspring. Furthermore, considering that the tardy jobs are scheduled at the end of the sequence, it may be sufficient to schedule the other jobs by minimizing the setup times. It is the aim of introducing the IP$_{TSP}$ intensification procedures.

The CBS column shows the deviations of the CBS approach minimizing the total tardiness defined in Section 3.2. For this approach, the execution time is limited to 60 minutes. It can be noticed that the CBS approach results deteriorate with increasing the instances size and especially for the **4, **5 and **8 instances. The GA$_{PCX}$ column shows the average de-

Table 1: Comparison of different algorithms.

PRB	*OPT*	*GA*	*CBS*	GA_{PCX}	GA_{IP}	GA_{HYB}
401	90	0.0	0.0	0.0	0.0	0.0
402	0	0.0	0.0	0.0	0.0	0.0
403	3418	0.5	0.0	0.0	0.4	0.0
404	1067	0.0	0.0	0.0	0.0	0.0
405	0	0.0	0.0	0.0	0.0	0.0
406	0	0.0	0.0	0.0	0.0	0.0
407	1861	0.0	0.0	0.0	0.0	0.0
408	5660	0.2	0.9	0.0	0.1	0.0
501	261	0.5	0.4	0.0	0.5	0.0
502	0	0.0	0.0	0.0	0.0	0.0
503	3497	0.2	2.5	0.0	0.3	0.0
504	0	0.0	0.0	0.0	0.0	0.0
505	0	0.0	0.0	0.0	0.0	0.0
506	0	0.0	0.0	0.0	0.0	0.0
507	7225	0.7	1.8	0.0	0.7	0.0
508	1915	0.0	35.8	0.0	1.8	0.0
601	12	169.4	41.7	6.7	7.5	3.3
602	0	0.0	0.0	0.0	0.0	0.0
603	17587	1.8	6.5	0.8	1.1	0.2
604	19092	1.8	21.1	1.1	1.3	0.6
605	228	13.0	122.4	2.6	3.5	0.4
606	0	0.0	0.0	0.0	0.0	0.0
607	12969	1.6	17.7	0.7	1.9	0.2
608	4732	1.7	156.6	0.7	1.2	0.0
701	97	30.7	20.6	6.8	8.3	2.1
702	0	0.0	0.0	0.0	0.0	0.0
703	26506	1.9	2.8	1.2	1.8	0.9
704	15206	3.4	94.8	1.6	2.1	0.5
705	200	33.7	72.5	6.1	6.5	2.2
706	0	0.0	0.0	0.0	0.0	0.0
707	23789	2.2	20.4	1.0	1.9	0.3
708	22807	2.8	50.0	1.5	2.1	1.2

viation of the genetic algorithm in which the crossover operator PCX is integrated. The probability p_{PCX} is equal to 0.2 and the CBS approach execution time is limited to 15 seconds. The GA_{PCX} average time execution is equal to 15.2 minutes for the 32 instances. The first observation is that the GA_{PCX} algorithm is always optimal for 15 and 25 jobs instances. It should be noted that the integration of the PCX crossover improves all of the GA results and especially for the instances **1 and **5 where the deviation became less than 7%. For example, the deviation was reduced from 169.4% to 6.7% for the 601 instance. Using the direct precedence constraints allows the PCX crossover to enhance both the GA exploration and the CBS search; and consequently reaching better schedules.

The GA_{IP} column shows the average deviation of the genetic algorithm in which we include the IP_{Tard} and IP_{TSP} intensification procedures under probability p_{IP} equal to 0.1. The CBS approach execution time is limited to 20 seconds for the IP_{Tard} and IP_{TSP}. The GA_{IP} average time execution is equal to 16.5 minutes for the 32 instances. The GA_{IP} improves most GA results and specially the **1 and **5 instances but gives worse results than the GA_{PCX} and this was expected because in 50% of the cases the intensification procedure minimizes the makespan and not the total tardiness.

The GA_{HYB} column shows the average deviation of the GA_{PCX} algorithm where we include the IP_{Tard} and IP_{TSP} intensification procedures. The probabilities p_{IP} and p_{cip} are equal to 0.1 and 0.5 respectively like the GA_{IP}. The CBS approach execution time is also limited to 20 seconds for the IP_{Tard} and IP_{TSP} in the GA_{HYB}. The GA_{HYB} average time execution is equal to 24.5 minutes for the 32 instances. This hybrid algorithm improves all the results found by the GA_{PCX}. These improvements are more pronounced with the integration of local search procedures. The introduction of the two intensification procedures improves essentially the **1 and the **5 instances. Also, the optimal schedule is always reached by GA_{HYB} for the 608 instance. The GA_{HYB} found the optimal solution for all the instances at least one time and this was not the case either for GA_{PCX} or GA_{IP}.

The convergence of both GA and the GA_{PCX} algorithms are similar. Indeed, the average convergence generation is equal to 1837 and 1845 generations for GA and GA_{PCX}, respectively. Concerning the GA_{IP} algorithm, the average convergence generation is equal to 1325 generations. So, we can conclude that the two intensification procedures based on the CBS approach are permitting a faster genetic algorithm convergence than the PCX crossover but achieving worse results. The GA_{HYB} average convergence generation is equal to 825 and compared to the GA_{PCX}, the introduction of the intensification procedures speeds up the convergence of the solution with reaching better results.

Exact methods are well known to be time expensive. The same applies to their hybridization of them with metaheuristics. Indeed, times execution increases significantly with such hybridization policies due to some technicality during the exchange of information between the two methods (Talbi, 2009; Talbi, 2002; Puchinger and Raidl, 2005; Jourdan et al., 2009) and this is what has been observed here. However, in this paper, the solution quality is our main concern. So, we concentrated our efforts on it.

5 CONCLUSIONS

In this paper, we describe the hybridization into a Genetic Algorithm of both a crossover operator and intensification process based on Constraint Based Scheduling. The PCX crossover operator uses the direct precedence constraints to improve the CBS search and consequently the schedules quality. The precedence constraints are built from the selected parents information in the reproduction process.

The intensification procedures are based on two different CBS approaches after fixing a jobs block : the first minimizes the total tardiness which represents the considered problem objective function while the second minimizes the makespan which also enhances the exploration process and is well adapted to some instances. These three policies hybridization represent the main contribution of this paper.

Compared to a simple GA, the use of the PCX crossover improves all the results but for some instances the difference is still noticeable. The hybrid algorithm which uses the PCX crossover and the intensification process improves the results and speeds up the convergence of the solution. These results suggest that the latter model seems to outperform the single GA, the genetic algorithm with the hybrid PCX crossover and the genetic algorithm with the intensification process.

A possible area of research in the future would be to improve the precedence constraints quality. Indeed, it is possible to consider constraints related to a jobs set or to intervals time and indirect constraint. Another possible area for further research would be to employ a chromosome representation based on the start times of activities. Hence, it will be possible to get more accurate combination of start times.

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