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Performance evaluation of a GRASP-based approach for stochastic scheduling problems

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A B S T R A C T

Stochastic scheduling addresses several forms of uncertainty to represent better production environments in the real world. Stochastic scheduling has applications on several areas such as logistics, transportation, production, and healthcare, among others. This paper aims to evaluate the performance of various greedy functions for a GRASP-based approach, under stochastic processing times. Since simulation is used for estimating the objective function, two simulation techniques, Monte Carlo simulation and Common Random Numbers (CRN), are used to compare the performance of different greedy (utility) functions within the GRASP. In order to validate the proposed methodology, the expected total weighted tardiness minimization for a single machine problem was taken as case study. Results showed that both, CRN and Monte Carlo, are not statistically different regarding the expected weighted tardiness results. However, CRN showed a better performance in terms of simulation replications and the confidence interval size for the difference between means. Furthermore, the statistical analysis confirmed that there is a significant difference between greedy functions.

1. Introduction

Scheduling problems are combinatorial optimization problems (COPs) encountered in logistics, transportation, production, healthcare, financial, and telecommunications, among others (Juan et al., 2015). Even though the deterministic version of COPs has been widely studied, their practical application is most likely hampered due to their disregard of uncertainty factors (Sarin et al., 2013). Consequently, stochastic scheduling tries to find solutions that optimize a performance measure under the assumption that uncertain parameters are random variables with known distributions (Sarin et al., 2013). Stochastic COPs (SCPOs), according to Bianchi et al. (2008), involve computing one or more expected values for evaluating the objective function. Hence, the objective function can be calculated based on closed-form expressions or estimated by simulation. If closed-forms expressions are available,

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the objective function can be computed exactly, although such procedure can be computationally expensive. Therefore, ad hoc and fast approximations can be used instead. The design of ad hoc approximations strongly depends on the problem, and there are no general rules to find efficient approximations of the objective function. If closed-form expressions do not exist, simulation can be used to estimate the objective function, particularly for complex problems in terms of decision variables and probabilistic dependencies. The objective function estimation is based on the outputs of the simulation model as follows: $f(\theta) = \mathrm{E}\,[L(\theta,\omega)]$, where θ is the vector of decision variables (in this case if a job is scheduled at a given position of the sequence), ω represents the set of values obtained for a determined realization of the stochastic processing times, and $L(\theta,\omega)$ is the objective function value obtained from the outputs of simulation realizations (e.g. the weighted tardiness for a specific realization of processing times) (Figueira & Almada-Lobo, 2014).

The use of hybrid simulation-optimization techniques has flourished in the last fifteen years or so, fertilized in large part by the increase in computational power, the development of advanced optimization methods and the emergence and dissemination of simulation software (Juan et al., 2015). According to (Figueira & Almada-Lobo, 2014), simulation-optimization methods can be classified considering the interaction between both techniques and the role of simulation. Thus, the simulation model can be used for solution evaluation (SE), analytical model enhancement (AME) or solution generation (SG). The first approach, SE, is the most popular and requires a simulation model to represent the system. The simulation model is used to evaluate the performance of various solutions (Alkhamis et al., 1999). In the second approach, a recursive process is executed between the optimization model (typically linear) and the simulation model. Simulation results are used iteratively to refine the parameter of the analytical model (Figueira et al., 2013). In certain cases, the optimization model can be solved first and that solution can be then simulated in order to compute all the variables of interest, hence simulation helps to generate and evaluate the performance of the whole solution (SG is also known as optimization-based simulation). There are two methods for SG depending on when the optimization process is performed: solution completion by simulation (SCS) or iterative optimization-based simulation (IOS). The former is a sequential procedure in which the analytical model is executed to generate initial solutions under ideal conditions. Then, the simulation model is run to complete or to achieve a better solution based on the initial solution provided by optimization (Alkhamis et al., 1999). Instead, in IOS, optimization is embedded in simulation, hence optimization may be called during simulation execution. As pointed out by (Dehghanimohammadabadi & Keyser, 2015), IOS models are not extensively studied and are very useful to handle stochastic models.

Particularly, in the IOS approach, the optimization strategy can be executed once for each iteration of the simulation model. This implies that in problems with large solution spaces, such as scheduling problems, metaheuristic procedures can be used to reduce the computing cost (Figueira & Almada-Lobo, 2014). Hence, the mixture of metaheuristics with simulation has become very popular in Operations Research as a good procedure to tackle difficult combinatorial optimization problems (Ferreira, 2012). In this context, one major drawback is that solutions are not expected to be optimal. Nevertheless, it is often preferable to obtain an approximate solution to an accurate model rather than the optimal solution to an oversimplified model (Juan et al., 2015). Furthermore, since the metaheuristic procedure solves several times the deterministic problem, it is reasonable to expect high correlation between the performances in both scenarios, stochastic and deterministic (Juan et al., 2014; Juan et al., 2015). Therefore, selecting an appropriate metaheuristic can be made on the basis of its performance when solving the deterministic version of the combinatorial optimization problem.

Among metaheuristics, GRASP (Greedy Randomized Adaptive Search Procedure) is an iterative multi-start metaheuristic for difficult combinatorial problems (Rajkumar et al., 2011). The GRASP Iteration consists of a construction phase and an improvement phase. The construction phase randomly builds a feasible greedy solution. When a feasible solution has been built, its neighborhood is explored in a local search phase until a local optimum is found. Hence, in each iteration, phase one generates a starting point and then, the local search of phase two is applied. The best overall solution, when a given termination criterion is met, is returned as the output (João et al., 2014). Compared to other metaheuristics, GRASP appears to be competitive with respect to the number of parameters to tune (only two: the size of the candidate list and the stopping criterion), the quality of the solutions, and the low implementation complexity (Rajkumar et al., 2011). Successful applications of GRASP to solve scheduling problems can be found in (João et al., 2014; Rajkumar et al., 2011; Rajkumar et al., 2010).

According to experiments conducted by Ribas and Companys (2015) and Niño and Caballero (2009) using GRASP, solution quality highly depends on the correct selection of the greedy function applied in the construction phase. Thus, in scheduling problems with uncertainty (variance), high quality solutions for the stochastic problem can be found by searching for high-quality solutions from the deterministic version of the scheduling problem. Therefore, experiments must be conducted in order to select the best greedy function for each stochastic problem realization. Particularly in scheduling problems, the use of stochastic processing times implies having several problem realizations to be able to analyze the effect of stochastic variations on solution performance. Usually, Monte Carlo simulations or Discrete-Event Simulations are applied to generate or evaluate those problem realizations (Juan et al., 2015).

Another alternative to the aforementioned simulation techniques is the common random numbers (CRN). CRN is a variance reduction method in which various alternatives are tested against the same random input streams. It is known that using common random numbers can increase efficiency of simulation procedures (Chen, 2012). The use of CRN is justified by the fact that Monte Carlo simulation might turn out in large computation times (Juan et al., 2015), while CRN can increase efficiency of simulation procedure and increase the probability of correct selection of the greedy function (Chen, 2012). Even though CRN has shown that the computational effort can be reduced on problems of different contexts (Nakayama, 2007), as far as the authors know there are no reports on CRN performance evaluation on production scheduling problems. Therefore, the main purpose of this paper is to evaluate the performance of various greedy functions for a GRASP-based approach, under stochastic processing times. To do so, a statistical method is presented to compare Monte Carlo simulation and Common Random Numbers (CRN).

2. Methods

The methodology presented in this section applies an Iterative Optimization-based Simulation (IOS) and it is adapted from the methodology proposed by (Juan et al., 2015). As mentioned before, two simulation techniques are used: Monte Carlo simulation and Common Random Numbers (CRN). Those techniques are used to generate the stochastic problem realizations, specifically for the processing times p_j, for each job $j \in \mathbf{J}$, as depicted in Fig. 1. Each problem realization is considered a deterministic scheduling problem, hence it can be solved by the GRASP-based algorithm. As it is shown in Figure 1, the main difference between using Monte Carlo or CRN is related to the evaluation of greedy functions. When using Monte Carlo simulation, a set of independent realizations must be generated for evaluating each greedy function. On the contrary, according to (Li et al., 2012), CRN allows the use of the same set of numbers for all greedy functions to be evaluated. In orde to evaluate the performance of both simulation approaches, a statistical method is required (Li et al., 2012). Thus, a final procedure is executed considering two chriteria: i) the relationship between the GRASP greedy function and the objective function of the SCOP, and ii) the relationship between the simulation approach and the expected interval size for $[\mu_a - \mu_b]$, where μ_a and μ_b are the expected value for the objective function, for greedy functions a and b, respectively. The hypothesis is that CRN technique allows reducing the number of simulation replications obtaining the same conclusions that can be inferred with a more computationally expensive Monte Carlo simulation.

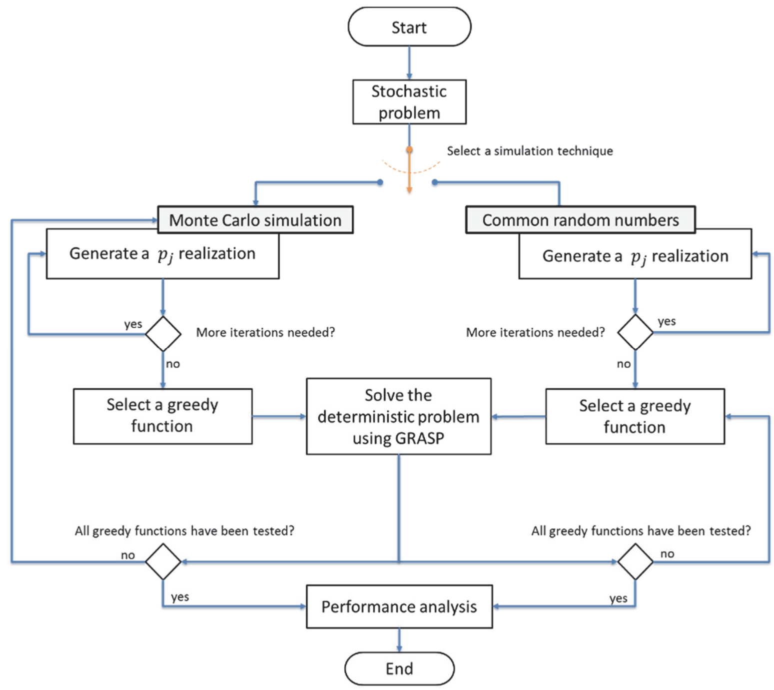

Fig. 1. Simulation-optimization approach. Adapted from (Juan et al., 2015)

In order to validate the methodology presented in Fig. **1**, the expected total weighted tardiness minimization for the single machine stochastic scheduling problem (SMSP) is taken as case study. The SMSP is classified as NP hard (Salmasnia et al., 2014) and is one of the most studied problems in production scheduling because of its complexity and practical importance (Lu et al., 2014). Recently, problems considering earliness-tardiness penalties have attracted much attention due to the reception of Just-In-Time philosophies in industry (Kayvanfar et al., 2013). However, according to Lu et al. (2014) even good solutions to the deterministic problem, lead to poor performance measures on real environments because of the variability of problem parameters, such as processing times, due dates, and arrival times. Thus, in the past decades, there has been a lot of interest to tackle the stochastic approach of the problem (Lu et al., 2014).

The SMSP can be defined as follows. Consider a set $\mathbf{J}$ of jobs that must be processed by one machine. All jobs are available at the beginning of the planning horizon and processing times ($p_j, j \in \mathbf{J}$) are stochastic. Only one job can be processed at a time and interrupt processing is not allowed. For each job $j \in \mathbf{J}$, its due date d_j and its weight w_j are known. Herein, the objective function of the scheduling problem aims for minimizing the expected total weighted tardiness $\mathrm{E}(1||\sum w_j T_j)$. Defining c_j as the completion time of job $j \in \mathbf{J}$, the tardiness of job $j \in \mathbf{J}$ can be calculated as $T_j = \max(0, c_j - d_j)$. Therefore, the objective function can be expressed as $\min \mathrm{E}(\sum_{j \in \mathbf{J}} w_j T_j)$ and the problem has been named as TWT-SMPS.

To evaluate the performance the SMSP with Monte Carlo simulation and CRN, data sets from the TWT-SMPS (*OR-Library*[1] by (Crauwels et al., 1998)) were extended to obtain a stochastic version of the problem. The data sets has 125 test instances available for three problem sizes $|\mathbf{J}|$=40, 50 or 100 jobs. There are three files wt40, wt50, and wt100 containing the instances of size 40, 50, and 100 respectively. Each file contains the data for 125 instances, listed one after the other. The processing times are listed first, followed by the weights, and finally due dates. However, since the data set proposes deterministic processing times, herein, processing times were assumed to follow a Log-

[1] Taken from: http://people.brunel.ac.uk/~mastjjb/jeb/orlib/wtinfo.html, August 25 of 2013

Normal distribution where Var $[p_j] = 2\ \mathrm{E}[p_j]$ for each job $j \in \mathbf{J}$, which, according to (Juan et al., 2014), implies high variability. Integer processing weights w_j were generated from the uniform distribution [1,10]. Instance classes of varying hardness were generated by using different uniform distributions for generating the due dates. For a given relative range of due dates RDD (RDD=0.2, 0.4, 0.6,0.8,1.0) and a given average tardiness factor TF (TF=0.2, 0.4, 0.6,0.8,1.0), an integer due date d_j for each job $j \in \mathbf{J}$, was randomly generated from the uniform distribution [P(1-TF-RDD/2), P(1-TF+RDD/2)], where $\sum_{j\in \mathbf{J}} p_j$.

Regarding the GRASP construction phase, three greedy functions were tested: weighted shortest processing time (WSPT) (Smith, 1956), weighted minimum slack (WMS) (Osman, Belouadah, Fleszar, & Saffar, 2009), and weighted modified due date (WMDD) (Kanet & Li, 2004). For the WSPT, job j should be processed before job k, whenever:

$$\frac{w_j}{p_j} < \frac{w_k}{p_k}. \tag{1}$$

The WMS rule orders the jobs according to the following expression. WMS selects the job with the weighted minimum slack at time t when the machine is available for non-scheduled jobs.

$$\frac{\max(d_j - p_j - t, 0)}{w_j}, \tag{2}$$

and last, the weighted modified due date rule (WMDD) in which jobs are processed in ascending order. Such assignment way is derived from Modified Due Date (MDD), in which jobs are scheduled by prioritizing those that have the earliest weighted due date regarding to the time t in which is evaluated. It is calculated as:

$$WMDD = \frac{1}{w_j}\left(max\{p_j, (d_j - t)\}\right). \tag{3}$$

To be able to compare simulation techniques, the sizes of the confidence intervals for $[\mu_a - \mu_b]$ were obtained for each instance under a specific scenario and simulation technique (Monte Carlo or CRN), considering a 95% of confidence. A full factorial experimental design was conducted to determine if, for the same scenario, there was a difference in the interval size between both simulation techniques. It will allow to determine if the results obtained using CRN technique are comparable with those obtained with Monte Carlo method. For the experiment, the response variable was the interval size for $[\mu_a - \mu_b]$, and the five factors considered were: the simulation approach with two levels (CRN or Monte Carlo), tardiness factor – TF with five levels (0.2, 0.4, 0.6, 0.8, 1.0), due date range – DDR with five levels (0.2, 0.4, 0.6, 0.8, 1.0), five scenarios with different number of replications (200, 400, 600, 800, 1000), and the three couples of greedy functions (WMDD-WMS, WMDD-WSPT, WSPT-WMS).

The complete simulation-optimization greedy randomized adaptive search procedure used for the stochastic single machine scheduling problem is described in Fig. 2.

3. Computational Results and Analysis

Contrary to the deterministic problem, for the stochastic problem analyzed herein there are no solutions reported in literature. Therefore, the following results and analysis are only focused on the performances achieved by both simulation approaches with the selected greedy functions. The GRASP was implemented on a computer with Intel(R) Core(TM) i7-3770, 3.40GHz, 3401 Mhz, with 4 main processors, 8 logic processors and 16 GB of RAM. A total of 75 instances, three for each combination of TF and DDR, each one with 40 jobs from the OR-Library were analyzed. Table 1 presents the results of the significant factors and interactions of the aforementioned experiment. The experiment took four weeks of continuous running.

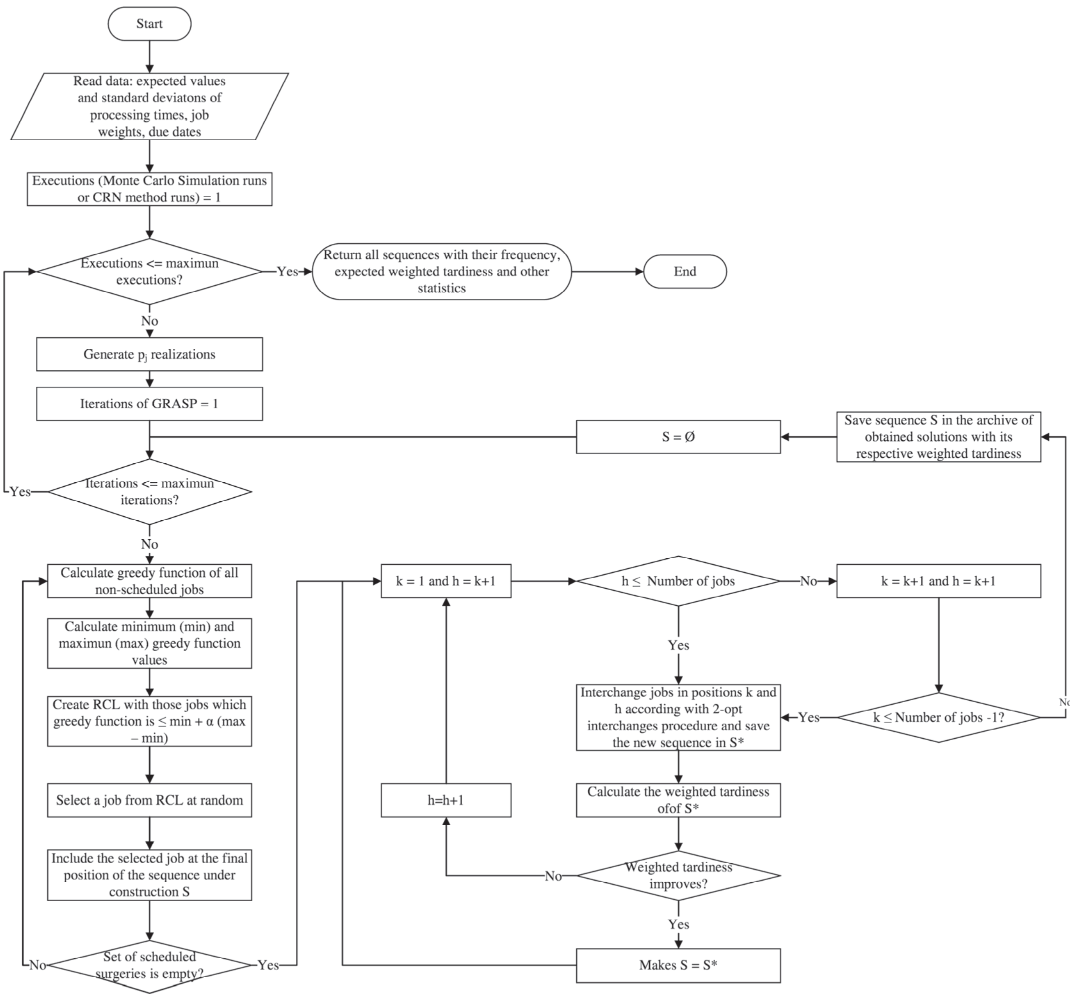

Fig. 2. Simulation-optimization GRASP procedure

Table 1
Best ANOVA of Expected interval size for $[\mu_a - \mu_b]$*

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Simulation approach	1	2641178932	2641178932	39285.23	0.000
TF	4	813414705	203353676	3024.71	0.000
DDR	4	2024660	506165	7.53	0.000
Scenarios	4	263251461	65812865	978.91	0.000
Simulation approach*TF	4	800695296	200173824	2977.41	0.000
Simulation approach*DDR	4	2003396	500849	7.45	0.000
Simulation approach* Scenarios	4	248945263	62236316	925.71	0.000
TF*DDR	16	37773846	2360865	35.12	0.000
TF*Scenarios	16	77667859	4854241	72.2	0.000
Simulation approach* TF*DDR	16	36559066	2284942	33.99	0.000
Simulation approach* TF*Scenarios	16	76886485	4805405	71.48	0.000
Error	2160	145218616	67231		
Lack-of-Fit	660	10184311	15431	0.17	1.000
Pure Error	1500	135034305	90023		
Total	2249	5145619585			

*Where μ_a, μ_b refers to the means of the objective functions found with two greedy functions

The adjusted coefficient of determination is 0.9706, which indicates that the studied factors: method of simulation, TF, DDR and scenarios explain the variability of expected interval size for $[\mu_a - \mu_b]$ in a 97%. Given that normality and homoscedasticity assumptions were not fulfilled, a Tamhane test was carried out. Tamhane results confirmed ANOVA outcomes. The fact that the method of simulation has a significant effect on the interval sizes implies that one of the methods gives more precise confidence intervals. In this case CRN presents the lowest mean which means that CRN gives, in average, more precise confidence intervals than Monte Carlo technique. Moreover, note that it is of most interest to analyze the interaction between the method of simulation and scenarios because it allows confirming the advantages of using less runs with CRN but maintaining the quality of results. From Fig. 3, the double interaction between the method and scenarios is evident. Hence, as the number of replications increase, the interval size in Monte Carlo simulation technique decreases, becoming closer to the interval sizes found with the CRN simulation technique. Contrary to Monte Carlo, CRN allows interval sizes to remain stable independently of the number of replications.

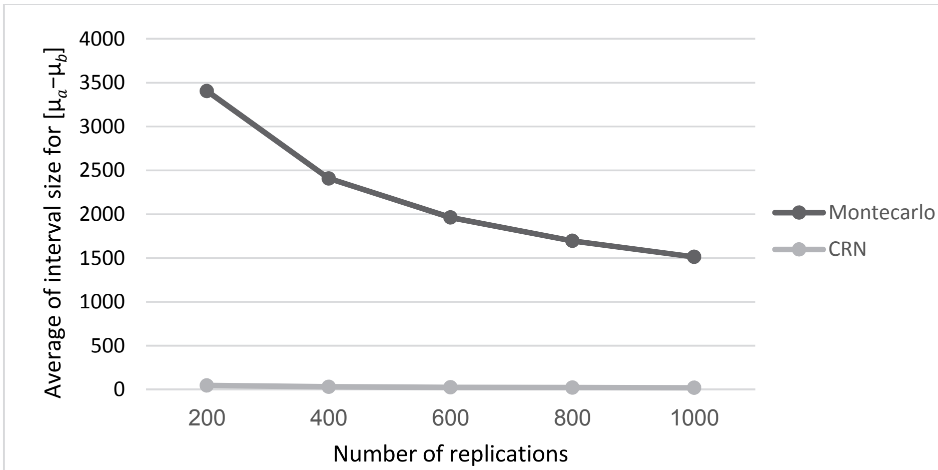

Fig. 3. Interaction plot Executions - Method

Another important double interaction is the TF-Method as seen in Fig. 4. CRN always achieved a reduced interval size for $[\mu_a - \mu_b]$, for all TF values. On the contrary, Monte Carlo did the same only for low TF levels. Thus, as the TF increases, Monte Carlo simulation fails to find a tight interval size.

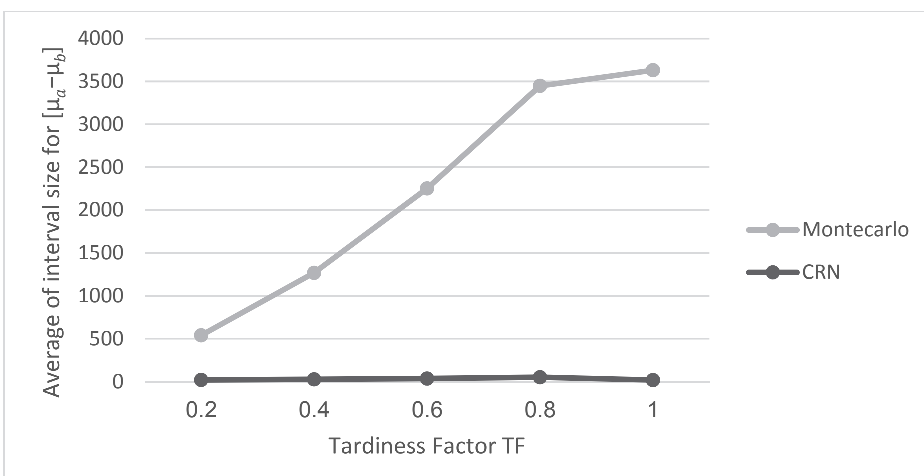

Fig. 4. Interaction plot TF – Method

The significant effect of TF and its corresponding interactions is normal depending on the tightness of due dates. As the tardiness factor increases the problem is harder because the probability of having more tardy jobs are higher since the due date becomes hard to be accomplished, whereas when TF is low, the problem is relaxed because many sequences present zero weighted tardiness. In order to establish the effect of the greedy function on the weighted tardiness expected value, a new ANOVA experiment was conducted using the *Instances* as a factor instead of the TF and DDR. The other factors, the simulation approach and the scenarios were kept. For this new ANOVA, the expected weighted tardiness values were taken as the response variable. Results of Best ANOVA shows that, although instances have the highest significant effect, the greedy function and the interaction between greedy function and instances also have a significant effect on the expected weighted tardiness, with a confidence of 95% (Table 2). This is important because in average there is a greedy function that statistically outperforms the other ones and because ones greedy functions are better for some instances than for others. This analysis of variance presents an adjusted determination coefficient of 0.998 which implies that the variability of expected weighted tardiness is explained by this factors and interactions in a 99.8%. Fig. 5 shows how the WMDD rule presents the best expected results

Table 2
Best ANOVA of expected total weighted tardiness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Simulation approach	1	20	20	3	0,071
Instances	74	3341060000000	45149439477	7438320000	0,000
Greedy function	2	2390100	1195050	196883	0,000
Instances * Greedy function	148	8168282	55191	9093	0,000
Error	2024	12285	6		
Total	**2249**	**3341070000000**			

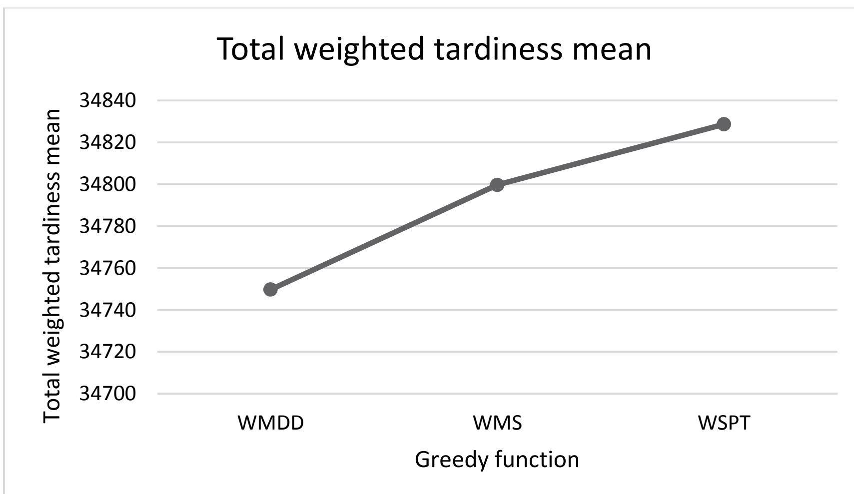

Fig. 5. Greedy function plot for weighted tardiness mean

4. Discussion and Concluding Remarks

A simulation-optimization method is presented for the solution of scheduling problems. For the simulation part, the Monte Carlo and CRN simulation techniques were implemented in order to establish the overall performance of the stochastic scheduling problem. For the optimization part, a GRASP metaheuristic was used and hybridized with the simulation technique. A case study based on a single machine problem with total weighted tardiness minimization was used for evaluating the performance of both approaches.

Results showed that CRN is better than Monte Carlo simulation, particularly for reducing simulation replications, and confidence interval sizes. Moreover, experiment results confirmed that greedy functions have a significant effect on the total weighted tardiness mean. In this case, the best results were obtained with the WMDD rule, which is similar to the results obtained in studies by (Kanet & Li, 2004; Molina-Sánchez & González-Neira, 2016), but for the deterministic case. Furthermore, the CRN approach also confirmed its capability to be used when comparing scheduling alternatives.

Future works will be focused on implementing CRN on other scheduling environments as flow shops or job shops, and with other objective functions. Likewise, other probability distributions and different variation coefficient levels will be taken into consideration.

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