Comparison of performance the neighborhood operators and the ratio of search local-global in minimizing makespan using an GA-VNS collaboration to solve reactive production scheduling

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Abstract--Reactive production scheduling involves searching methodologies in a wide solution space. A criterion often used in the analysis of results for this type of problem is makespan. Many artificial intelligence techniques are being used in an attempt to minimize the makespan. The use of global and local search hybridization has been well referenced. Usually the each global search for a solution applies some local searches in the same solution, trying to find a better solution in the neighborhood. These local search operations have used neighborhood operators.This paper has two research objectives: investigation of the better neighborhood operator and the better ratio local/global. This proposal implements a hybrid Genetic Algorithm (GA) with Variable Neighborhood Search (VNS). The proposal was validated in three scenarios of Job Shop Scheduling (JSS) coming from Taillard base and using three neighborhood structures.

Keywords -- local search, hybridization, neighborhood operator, ratio local/global.

I. INTRODUCTION

Presently the manufacturing industries have undergone tremendous changes due to the increased use of process technologies, such as industrial robots, machine tools, computerized numerical control, handling systems and transport of materials [1].

This context indicates a change in focus that places the manufacture no longer as a simple support area, but as a member of the group of factors determining competitiveness. In this environment, the manufacturer must be evaluated on its strategic dimensions, such as cost, quality, service and flexibility [2].

The problem of production planning (PP) is the allocation of resources in time and in the correct sequence, so that the result is the completion of all tasks in the shortest time possible (makespan) [2]. This problem is NP-hard, i.e., the computational cost grows exponentially with the size of the problem [3].

Another point to be considered is the time to get the solution, i.e. the PP problem will not be considered as planning task, but as a control one. This means that the problem of this work is, in fact, a reactive production scheduling problem.

Among the possibilities to solve this problem there is the use of artificial intelligence techniques. Several approaches proposed for addressing the problem of scheduling indicate a high efficiency in the use of genetic algorithms (GA) [4-7].

New approaches suggest the conjunction of a global search method with a local search method [8-14]. The Hybridization of genetic algorithm with VNS has shown promise in some studies [15-18].

In many articles, the Natural Representation (NR) is used as neighborhood structure (NS) [21][25]. The NR is a single list cointaining the respective machine assignment of the n jobs [26]

In others the Critical Path (CP) is used as NS [22][24]. Critical Path is the subset of operations of programming operations starting at time zero and ending at the same time of the makespan, whose operations are critical, because its delays increases the overall makespan of the schedule [27].

Other NS are found, based on CP or RN.

Another NS is the SSDT (Search in Spanning Tree) [20] that has high correlation with the makespan.

In local search, three neighborhood operators are commonly used: insert, swap and 2-opt [21-22][24-25], usually being the three used together and with a fixed number of times each.

But it is not evident whether any of them have better performance.

Another point is the relation among the number of operations in a local search and the number of operations in a global search(ratio local/global).

There aren't studies indicating some more efficient relationship than the other. this work compared the ratios of 1, 5, 10 and 30 for local search / global search.

Within this context, this paper proposes to find the better neighborhood operator to the problem of JSS, with time restriction for processing, using the genetic algorithm with VNS. Proposes still find the better ratio local/global among 1, 5, 10 e 30.

II. PROPOSAL

The purpose of this study is to verify the quality of the neighborhood operators commonly useds and the better ratio of operations in local search and global search operations.

Experiments are made using a GA-VNS collaboration with three neighborhood structures and three job shop scenarios of different sizes coming from Taillard [23], in context reactive production scheduling problem.

III. IMPLEMENTATION USING HYBRID GA WITH VNS

The problem of reactive production scheduling includes several products that can be produced through several different forms. What is sought is a series of products to be followed in production such a way that corresponds to a desired performance goal. Several performance measures are used today, and this paper uses the minimum makespan objective.

There are some assumptions in the proposed system, same used in comparisons, namely:

- Each machine operates only one product at a time and each product can only be operated by one machine at a time;
- The times of production are deterministic and known in advance;
- The setup times and transportation times are included in the time of production;
- A job starts transporting the raw material from the load sector to the input buffer of the first machine in your routing;
- A job ends up at the finished product transportation from the output buffer of the last machine to the unload sector;
- Machines do not stop or are defective;
- Every machine has an input buffer and output buffer size large enough to support any claim.

The parameters in GA and VNS were defined based in researchers's experience.

A. Genetic Algorithm

Genetic Algorithm is a biological inspirated meta-heuristic [19]. This principal characterist is a global search using randomic generation of solutions.

The Genetic Algorithm parameters used are:

Population of 30 individuals;

Chromosome: each gene is an operation and indicates the task to whom it belongs.

The chromosome used in this paper is illustrated in Figure 1. This chromosome indicates the sequence of operations that will be executed according to the scheduling, where:

Position 1: Product 1 in operation 1 starting in time t1;

Position 2: Product 2 in operation 1 starting in time t2;

…

Position 12: Product 3 in operation 3 starting in time t12.

Where ti <= tj for all i < j.

- Selection for new population: 1 by elitism and 9 per roulette;
- Crossover: 20 individuals making the exchange of segments between 2 chromosomes, as illustrated in Figure 2. Crossover one point ((first half of a raffled chromosome among the 10 betters and second half a raffled among the 20 worst).

The way to operate the crossover is as follows:

The first segment of first parent is copied for offspring.

Erased all operations that are commons among the second parent and the offspring. The remaining operations are copied to the offspring. This crossover grants that this chromosome is feasible.

1	2	1	3	2	1	2	3	2	3	1	3

Fig. 1. chromosome used.

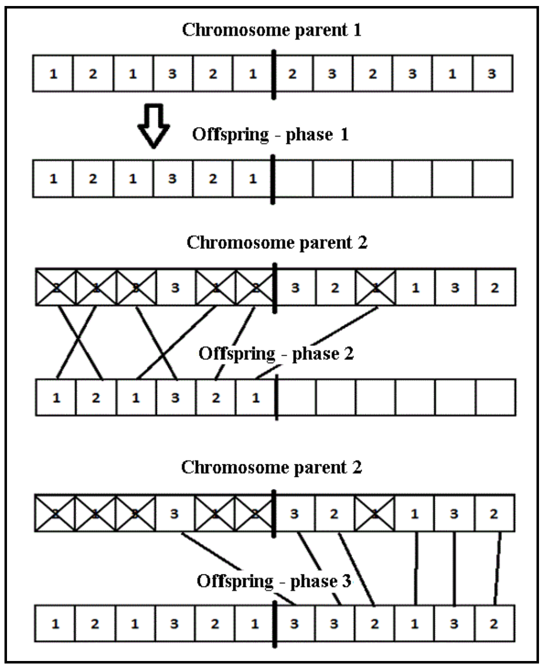

Fig. 2. crossover operation.

- Mutation: 3 individuals per generation, operating with operator 2-opt to creation of a new chromosomes.
- The fitness of each chromosome used in the genetic algorithm is obtained by the equation (1):

$$F(i) = \frac{1}{mkp_i} \qquad (1)$$

Where: F(i) is the fitness function of chromosome i and mkpi is the makespan of the same chromosome.

- Stopping criterion: three hundred seconds.

B. *Variable Neighborhood Search*

VNS search is a meta-heuristic method [15-16] and many researches have used it to solve scheduling problems. One of its principal characteristics is a use of many operators of neighborhood.

In this work, three operators (swap, insert and 2-opt) are used and variable iterations of each according to the specified in the experiments. The operators were chosen because they are the most cited in the literature.

VNS parameters:

Neighborhood Operators: insert, swap and 2-opt;

Number of iterations per operator = variable.

The figures 3, 4 and 5 explains the operators insert, swap and 2-opt.

Insert operator - A operation is deleted in a random position and re-inserted in other aleatory position.

Swap operator – select 2 operations in 2 random positions and exchange it.

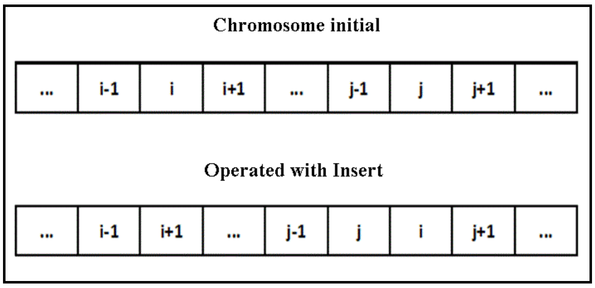

Fig. 3. insert operator.

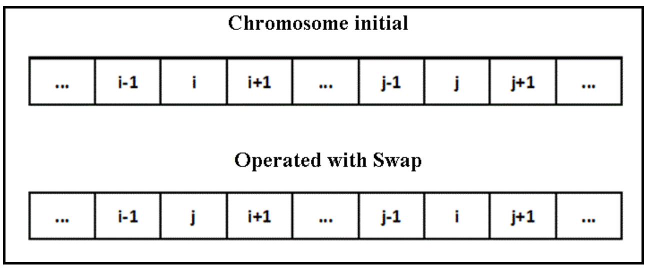

Fig. 4. swap operator.

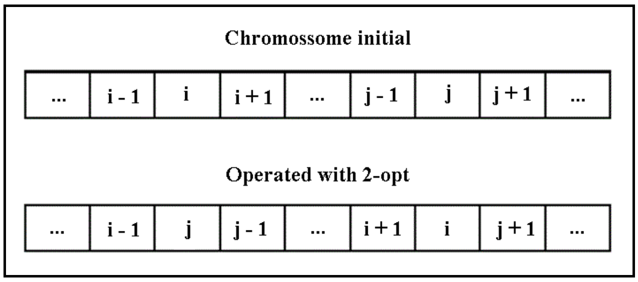

Fig. 5. 2-opt operator.

2-opt operator - The stretch between two randomly chosen positions is reversed.

C. *Hybridization pseudocode*

Step 1: Generate randomic initial population;

Step 2: All individuals are submited to a local search;

Step 3: Crossover: replace the 20 worst individuals by new chromosomes of crossover;

Step 4: Mutation: replace the the 3 worst individuals by new random chromosomes. (Elitism: keeps the best chromosome);

Step 5: If completed 300 seconds, return the best solution, otherwise go back to Step 2.

IV. COMPUTER EXPERIMENTS

Two experiments were done. The first seeking to identify the best neighborhood operator and the second seeking to identify the best ratio between the local and global searches, ie, how many local searches for each solution that has undergone a global search.

The scenarios come from base Taillard [23] and are the scenarios (jobs x machines) ta01(15x15), ta31(30x15) and ta61(50x20) that are in problemsinstances/scheduling/ jobshopscheduling and are just the first in each specification in job shop scheduling.

The Neighborhood structures used are the Representation Natural (RN), the Critical Path (CP) and the Search in Spanning Tree (SST). The first neighborhood structure and the second neighborhood structure are well known. The third neighborhood structure is showed in [20] based in tree coverability.

In the tables are presented, in addition to the average makespan of the executions, the p-values associated with t-student hypotheses tests done. The tested hypotheses will be explained in sections of each experiment.

For more reliability of the results it was used one statistical test, the t-student test for average of two independent populations with unknow variance.

In the first experiment are tested four neighborhood operators's settings, three the scenarios and three neighborhood structures, generating 36 lists with 35 data each. Each operator configuration runs 30 times in each local search.

The setting of neighborhood operators that appears to be the best is compared with the other three settings to confirm this hypothesis.

In the second experiment the best configuration of Experiment 1 is tested in the same three scenarios and the same three neighborhood structures, varying the number of times that the best configuration of Experiment 1 operates every global search, ranging from 1x to 30x, generating 36 lists 35 data each. The ratio among local and global search that appears to be the best is compared to the other reasons for confirmation of the hypothesis.

A. *Experiment 1*

This experiment aims to identify what neighborhood operator, among insert, swap and 2-opt, that gets better results (makespan) when used in a GA-VNS collaboration to solve reactive programming problems.

For such, are compared results using four settings of neighborhood operator: All - with 3 operators running 10x each; Insert - with the insert operator running 30x; Swap - with the swap operator running 30x; and 2-opt - with the 2-opt operator running 30x.

Each configuration operator (4) performs 35 times in each scenary (3) and in each of the three neighborhood structures. (4 x 3 x 3 = 36)

In total were executed 36 batteries of 35 runs each. The main results of these batteries, the average makespan of 35 runs and p-value of comparisons, are presented in the following tables.

Comparisons are made for each set of operators settings, and at the end we have 9 lines of comparison, comparing the results of these settings for each pair of scenario and structure of neighborhood.

Each table shows the results for each scenario, distributed into 6 rows of data, 2 for each structure of neighborhood. The first line shows the average makespan of 35 runs, the second line shows the p-value of t-student test made.

Analyzing the three tables can be seen that most of the best results were obtained by the neighborhood operator 2-opt (7 of 9). So this happens to be the leading candidate the best operator of neighborhood.

Was elaborated for each comparison the null hypothesis that the results achieved by competitors configuration are better than the results of 2-opt operator. Applies the t-student hypothesis test for means of two independent populations with unknown variances and was obtained the corresponding p-value.

If this p-value is less than 0.05 indicates that one can say with 95% confidence that the results of 2-opt are smaller than the results of the competitors. If the p-value is greater than 0.05 and the average 2-opt is smaller than the competitor can say with 95% confidence that both are equal. If p-value is greater than 0.05 and average 2-opt is greater than the competitor concludes with 95% confidence, that the competitor results are smaller or equal than 2-opt, where necessary an additional test to confirm whether they are equal.

This additional null hypothesis verifies if the two averages are equal and if p-value is greater than 0.05 are considered equal, otherwise it is considered the results of the operator 2-opt as greater.

In Table 1 it can be seen that the averages of 2-opt are smaller in eight of nine comparisons and, statistically, is confirmed that 5 are better and the other 4 being equal. It was necessary to use an additional test, in comparison with the result marked with an asterisk, and obtained p-value = 0.9368.

In table 2 it can be seen that the averages of 2-opt are smaller in seven of nine comparisons and, statistically, is confirmed that six are better and the other three are equal. It was necessary to use an additional test in two comparisons, the results marked with an asterisk, and there was obtained p-values 0.2679 and 0.1463.

In Table 3 it can be seen that the averages of 2-opt are smaller in nine comparisons and, statistically, is confirmed that nine are better.

In analysis, these three tables permits concluded that the 2-opt operator has better results than other configurations of neighborhood operator, given the context and applied with 95% confidence.

TABLE I. EXPERIMENT 1 IN SCENARY 15 X 15.

		Operator setting			
		All	**Insert**	**Swap**	**2-opt**
RN	**Average**	1325,03	1334,14	1332,58	1323,46
	P-value	0,2880	0,0013	0,0032	
CP	**Average**	1325,46	1330,86	1332,71	1321,63
	P-value	0,1017	0,0042	0,0013	
SST	**Average**	1318,2	1326,31	1317,71*	1317,94
	P-value	0,4583	0,0008	0,5316	

TABLE II. EXPERIMENT 1 IN SCENARY 30 X 15.

		Operator setting			
		All	**Insert**	**Swap**	**2-opt**
RN	**Average**	1966,03	1989,86	1983,74	1958,54
	P-value	0,0414	1,58E-09	2,38E-06	
CP	**Average**	1963,97	1975,28	1970,54	1958,17
	P-value	0,1235	0,0015	0,0039	
SST	**Average**	1956,86*	1971,34	1955,17*	1960,2
	P-value	0,3120	0,0032	0,9268	

TABLE III. EXPERIMENT 1 IN SCENARY 50 X 20.

		Operator setting			
		All	Insert	Swap	2-opt
RN	Average	3251,91	3302,6	3294,46	3219,4
	P-value	3,42E-07	4,83E-19	9,60E-21	
CP	Average	3283,4	3289,28	3291,28	3257,91
	P-value	0,0011	5,92E-05	1,12E-05	
SST	Average	3237,43	3280,86	3265,03	3218,83
	P-value	0,0009	1,16E-14	1,64E-11	

B. Experiment 2

In implementation made, every generation of GA population of chromosomes (solutions) suffers global search operations and each chromosome (solution) is subjected to VNS and undergoes a number of operations in the neighborhood.

This experiment aims to identify the best ratio between the number of operations in a solution made by local search and the number of operations performed in the global search.

Was defined four work ratios: R1, R5, R10 and R30 indicating that respectively 1, 5, 10 or 30 local operations for one global operation.

Other ratios (3, 15, 20, 40 and 50) were tested too, but the results are approximate to results for the ratio immediately below.

Remember that in the Experiment 1 was used the ratio 30.

This experiment uses the conclusion of Experiment 1 confirming that the neighborhood operator 2-opt operates better in this context and uses it as the neighborhood operator in Experiment 2.

Each configuration ratio (4) performs 35 times in each scenary (3) and in each of the three neighborhood structures (4 x 3 x 3 = 36)

In total, were executed 36 batteries 35 runs each. The main results of these batteries are presented in the following tables.

Comparisons are made for each set ratio settings, and at the end we have 9 lines of comparison, comparing the results of these settings for each scenario and each neighborhood structure.

Each table shows the results for each scenario, distributed into 6 rows of data, 2 for each neighborhood structure. The first line shows the average makespan of 35 runs and the second line shows the p-value of t-student test.

Analyzing the three tables can be seen that most of the best results were obtained by the ratio R10 (9 of 9). So this happens to be the leading candidate the best ratio.

Was elaborated for each comparison the null hypothesis that the results obtained by competitor configuration are better than the results of the R10 ratio. Applies the t-student hypothesis test for average of two independent populations with unknown variances and was obtained the corresponding p-value.

The process of analysis is the same that was used in Experiment 1. The first null hypothesis compares the R10 and the competitor to verify if the competitor is smaller or equal than R10. The second null hypothesis compares the R10 and the competitor to verify if are equals.

In Table 4 it can be seen that the averages of R10 are smaller in all comparisons and, statistically, is confirmed that 3 is better and the other 6 are equal.

In table 5 it can be seen that the averages of R10 are lower in 8 of 9 comparisons and, statistically, is confirmed that 6 are better and 3 are equal. It was necessary to use an additional test in one comparison, the result marked with an asterisk, and there was obtained p-value 0.4917.

In Table 6 it can be seen that the averages of R10 are lower in 6 of 9 comparisons and, statistically, is confirmed that 4 are better and 5 being equal.It was necessary to use an additional test in three comparisons, the results marked with an asterisk, and there was obtained p-values 0.6627, 0.6366 and 0.5613.

In analysis, these three tables tables permits concludes that the R10 ratio, better at 11 and equal at 7, has better results than other ratios, given the context and applied with 95% confidence.

Also was performed the same Experiment 2 for operators Insert and Swap and was confirmed in both that the 2-opt operator and the ratio R10 gets better results. These data were not placed on the article for reasons of space.

TABLE IV. EXPERIMENT 2 IN SCENARY X 15.

		Ratio LS/GS			
		R30	R5	R1	R10
RN	Average	1323,46	1322,80	1322,86	1322,11
	P-value	0,3302	0,4100	0,3956	
CP	Média	1321,63	1323,31	1326,83	1320,89
	P-valor	0,4053	0,2020	0,0214	
SST	Média	1317,94	1321,40	1321,63	1314,63
	P-valor	0,0990	0,0118	0,0031	

TABLE V. EXPERIMENT 2 IN SCENARY 30 X 15.

		Ratio LS/GS			
		R30	R5	R1	R10
RN	Average	1958,54	1948,37*	1952,57	1951,17
	P-value	0,0274	0,7541	0,3780	
CP	Average	1958,17	1952,11	1953,83	1945,37
	P-value	0,0079	0,0885	0,0434	
SST	Average	1960,20	1956,74	1967,86	1949,89
	P-value	0,0034	0,0475	5,60E-05	

TABLE VI. EXPERIMENT 2 IN SCENARY 50 X 20.

		Ratio LS/GS			
		R30	**R5**	**R1**	**R10**
RN	**Average**	3219,40	3210,46*	3219,20	3213,29
	P-value	0,1453	0,6686	0,1612	
CP	**Average**	3257,91	3233,80*	3249,00	3237,03
	P-value	0,0030	0,6817	0,0364	
SST	**Average**	3218,83	3206,66*	3235,46	3209,71
	P-value	0,0482	0,7193	8,37E-05	

V. CONCLUSION

The purpose of this paper is to answer two questions: among three neighborhood operators some stand out? Among four ratios of operations in local search and global search some stand out?

Experiments are made using a GA-VNS collaboration with three neighborhood structures and three job shop scenarios of different sizes and the limitation of 300 seconds of processing time.

The neighborhood operators compared were the Insert, Swap and 2-opt and the Experiment 1 confirmed that the 2-opt is better or equal to other operators tested with 95% confidence.

The ratios that were compared are 1/1, 5/1, 10/1 and 30/1 and the Experiment 2 showed that the ratio 10/1 was the one that had the best performance with 95% confidence.

The contributions of this paper is to highlight the quality of neighborhood operator 2-opt and the quality of ratio of 10 operations in the neighborhood for each global operation in context reactive production scheduling problem.

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