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Analysis of Job Shop problem through an expert system

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Abstract

In the present work it is defined a new methodology, based on Experts Systems, for sequencing in Job Shop Environments. This work is developed in two phases. In the first one, the different techniques used are defined. In the second one, the necessary statistical tests are executed.

The results show that the new technique don't produce an optimal result every single time; but in few seconds, this technique can find sub-optimal solutions with an approximation of 92.95 % and 73.88%, to the optimal solution, in the variables of total process time (makespan) and total idle time, respectively. Finally, the new technique is compared with other similar techniques.

1. Introduction

Since 1980, researches in the field of artificial intelligence have focused on the use of classic logistics as a knowledge representation. This last aspect has permitted that several enterprises have designed Expert Systems, allowing the productivity improvement and, both declarative and control time, money and knowledge optimization (Weiming et ál, 2006).

In general, an Expert System may be defined as a software that imitates the behavior of a human expert in a specific problem solving (Nebendahi, 1988). Thus, these systems can resolve problems in different fields as: industry and commerce (Weiming et ál, 2006), agriculture (Nebendahi, 1988), production programming, conforming of production orders (López, Médina, 2009), product design, investment planning, sea navigation (Rancán, 2004), risk and experimental time reduction, incorporation and fusion of simulation models results from different sources and disciplines, building automation (Sierra, et ál, 2005) systems planning, production scheduling in Job Shop environments (Nilgu¨n et ál, 2009; Adil, Mustafa, 2009), optimization (Zhang, Xiaoping, 2009), makespan minimization (Pei-Chann, 2009; Roshanaei, 2009) and all kind of applications in general (Savkin, Somlo, 2009; Giovanni, Pezzella, 2010; Chao-Hsien, Han-Chiang, 2010; Zhang, Xiaoping, 2009).

Nowadays, Expert Systems used in the medical domain as MYCIN, INTERNIST and NUCES exist, which have been ameliorated for a more efficiency accomplishment in terms of profits and prediction. Likewise, another type of Experts System as DRPC and DHI, contains a large database that permits orientate those who consult the monitoring and control of diverse aspects of milk production system and takes decisions about the dairy herd management. Explicitly, in the LEGAL field, Expert Systems have been designed (Gómez et ál, 2011) what have allowed assisting the justice operators (judges, district attorneys and defense lawyer) in the sentence individualization process, achieving a preliminary agreement between the parties.

Nevertheless, despite of the enormous Experts Systems use, it is important to stand out that its application in production systems, under Job Shop environments, has not been mainly spread; hence, its application and comparison with other techniques, is the central objective of this paper.

Expert Systems must incorporate and accumulate information, what makes them more efficient (in generational terms) and turns them as a valuable tool for decision taking. An Expert System must have the following characteristics: (a) to use a specific, symbolic ant mathematic knowledge, (b) to use methods of specific domain, heuristics and algorithmic. (c) to develop activities as specialist in the problematic area, (d) to express answers in a clear way (e) to be flexible (Zattar, et al. 2008). Besides, these systems must be formed by the following basic components: knowledge base, inference engine, coherency control, user interface and acquisition components.

Finally, in this point is determined that the Experts Systems only make sense with computerized tool assistance, what is incompatible with the great change resistance existing in developing countries, characterized by a low computing culture, where is no need of modifying its traditional production programming way (Sev, et al. 2008).

With this paper is expected to motivate the use of artificial intelligence techniques (Expert System) in low developed countries, where its production systems are manual, with short competitive levels (Arce, et ál 2000.).

2. Methodology

Even though the Intelligent Systems have been applied in diverse ways in Job Shop problem solving, in this section it is proposed and compared a new methodology based on Expert Systems, with other exiting methodology.

Step 1: Representation. Taking as reference some writings (Koonce, 2000), the Job Shop problem NxM, may be represented through a structure: machine, makespan, like the one illustrated in Table 1.

In Table 1, each column represents an order makespan (N) in the different work centers WC. In this case, every order is supposed to pass through the work centers, regardless of the arrange and with a process time $\mathbf{P}_{\mathbf{m,n}}$.

Table 1. NXM JSSP Representation**.**

Center	**Orders**							
	1	2	3	4	5	6	…	N
1	Tp_{11}	Tp_{12}	Tp_{13}	…..	…..	…	…	Tp_{1N}
2	Tp_{21}	Tp_{22}	**…**	…..	…..	…	…	Tp_{2N}
3	…	Tp_{32}	Tp_{33}	….	…..	…	…	**…**
…	…	**…**	…	…	$\mathbf{P_{m,n}}$	…	…	
M*C	Tp_{MC1}	Tp_{MC2}	Tp_{MC3}	….	….	…	…	Tp_{MCN}

Step 2: Sequencing. Process Sequencing is codified inside a matrix of C*N cells, where each column value $V_{m,n}$ of the matrix, represents the arrangement of attendance of every order N in a Work Center C, that is to say the order route (Table 2).

Table 2. Order routes.

Cent	**Pedidos**							
	1	2	3	4	5	6	…	N
C1	4	3	..	..	..	..	..	5
C2	3	2	**..**	..	..	..	..	4
…..								**M**
C3	2	1	..	..	..	..	..	**3**
C4	1	**M**	..	..	$\mathbf{V_{m,n}}$	..	..	2
…	..	..	..	..	..	..	..	..
$\mathbf{C_5}$	M	5	..	..	..	..	..	1

Step 3. Knowledge Base *KB*. Database initial records are composed by every one of the orders to sequence, the process time, the delivery time and the definition of every priority and artificial intelligence rules. These rules will be used in the problem solution, under this methodology: less makespan, more makespan, less time to complete a job, more time to complete a job, less time to initiate a job, more time to initiate a job, genetic algorithms, data mining, tabu search and other techniques as intelligent agents (Castrillon, et al. 2009).

Step 4: Inference mechanisms IM: the system must choose the most appropriate techniques combinations for the problem solution. These are chosen taking as reference the value provided by the adjustment module and by the current status of the variable total process time (Makespan).

Step 5: Coherence Control CC. In algorithm evolution, based on Artificial Intelligence technique, is feasible to generate some no valid solutions. In other words, not every order passes through the different work centers just one time. It is important to control these situations, in order to avoid absurd conclusions on the system's side. This last aspect will allow selecting just the valid solutions of the considered problem (Table 3).

Table 3: Possible solution to the problem. Gene's representation.

1	2	3	4	5	6	…	N
2		..	..	..	..	..	M
3	1	**..**	..	..	..	..	
8							
7	M	..	..	..	..	..	**3**
4		..	..		..	..	
..	5.	..	..	..	..	..	..
M		..	..	..	..	..	1

Step 6: Gantt. For each found solution in the previous step, a Gantt diagram is defined, which establishes the process arrangements in time and in every machine. Given this chart, the next activity is to evaluate each one of the different solutions, in order to calculate the total process time (makespan), and the total idle time. To accomplish that, next functions (Fitness) must be used:

$$Fitness_{makespan} = \min(\max_{1<=i<=N}(\max_{1<=j<=M}(P_{ij}))) \quad (1) \qquad Fitness_{idle} = \min\sum_{j=1}^{m} f_j \quad (2)$$

Given that the idle time is a total process time direct sequence, the fundamental objective is to minimize the fitness function. Where ***N*** represents the number of jobs. ***M*** is the number of machines. $\boldsymbol{P_{ij}}$ is the makespan of the job ***i***, in the machine ***j*** and $\boldsymbol{f_j}$**,** is the total ***m*** idle time of the machine ***j***.

Step 7: **Optimum.** Subsequently, it is necessary to calculate the optimum solution. This will allow calculating the approximation to the found solutions regarding the best one. In the same way, it will permit determining the proposed methodology effectiveness and will establish the approximation percentage of each one of the solutions found, regarding the general optimum.

Step 8: In order to guarantee the proposed methodology's consistency, it is necessary to repeat this methodology during a defined number of times (treatments). In every treatment, the best 10 results, with regard to fitness functions (Makespan), are taken as reference. To determine if results statistically coincide with equal or different treatments, a variance analysis is executed under the following model: $y_i = \mu + \mathrm{T}_i + \varepsilon_i$, where y_i represents the answer variables, T_i, the effects caused by the treatment i^{th}, and ε_i, is the i^{th} experimental error. At this point, it is important to verify that the recollected information accomplishes the necessary independence and normality conditions, which permits the application of required tests. Finally, by means of components acquisition and the respective user interface, the system must interact with its users.

3. Experimentation

In this methodology's experimentation, an answer from the metal mechanic sector was captured, about their fundamental product named "*bars*". Even though in the original problem the product must pass through five work centers, regardless the arrangement; experimentation was done based on a general type problem, with ***9*** work centers and ***16*** orders. Restriction caused by computational reasons. Table 4, illustrates the 16 orders makespans in each work center or machine:

Table 4. Process Times (Makespans). 1,0911x10^50 possible solutiuons.

C	**Orders**															
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
1	3	3	5	4	5	5	7	3	9	3	3	5	4	3	3	4
2	3	7	3	4	5	7	4	7	8	4	4	3	3	4	5	6
3	5	8	4	5	5	6	3	3	7	3	3	4	4	4	6	5
4	3	6	4	3	5	5	5	8	3	8	4	6	5	3	6	7
5	8	5	3	6	5	4	6	7	4	6	5	5	3	4	5	6
6	3	7	5	4	5	3	7	6	5	4	4	4	6	5	4	6
7	5	8	4	7	5	7	8	4	6	4	6	3	3	6	5	5
8	3	6	5	4	5	6	3	3	4	7	4	4	4	5	6	7
9	8	5	3	5	5	3	4	5	4	8	5	3	3	4	5	6

4. Results

Steps 1-6: Although best found solutions are good (Table 5), they are lightly far from total process time and total idle time variables, found in the optimal solution (Figure 1).

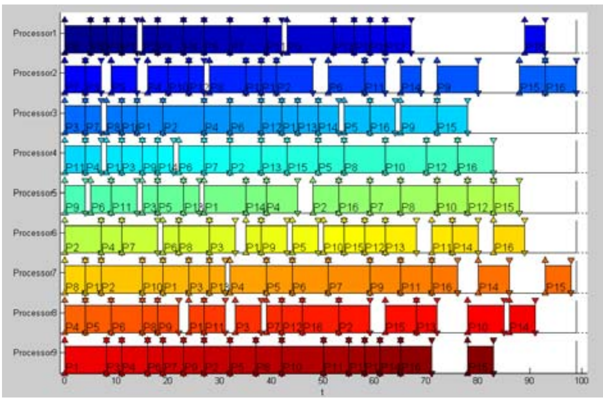

Figure 1. Optimal. T. Process = 99. Idle Time= 191.

Steps 7-8: In view of the fact that the methodology does not always provide the optimal solution, it is indispensable to estimate found solutions effectiveness when executing the correct algorithm, during 3 treatments of 10 consecutive repetitions. Gantt chart of the best one of found solutions in Tables 5 and 6, is illustrated in Figure 2:

Table 5. Makespan variance analysis

T Makespan					**Repetitions**						**Sum**
JSSP 3X9	1	2	3	4	5	6	7	8	9	10	
Treat 1	103	108	107	108	106	106	106	105	103	106	**1058**
Treat 2	108	108	107	106	107	106	107	107	105	107	**1068**
Treat 3	107	108	107	106	108	106	107	108	106	106	**1069**

Variance Source	**G L**	**SC**	**CM**	**Fcal**	**F Table**
Total Sum		49,50			
Treatment	2,00	7,40	3,70	2,37	3,35
Experimental Error	27,00	42,10	1,56		
Total	29,00	49,50	5,26		
INSIGNIFICANT MODEL					

Table 6. Idle time variance analysis

Idle Time JSSP 3X9	1	2	3	4	5	6	7	8	9	10	Sum
Treat 1	227	272	263	272	254	254	254	245	227	254	**2522**
Treat 2	272	272	263	254	263	254	263	263	245	263	**2612**
Treat 3	263	272	263	254	272	254	263	272	254	254	**2621**

Variance Source	**G L**	**SC**	**CM**	**Fcal**	**F Table**
Total Sum		4009,50			
Treatment	2,00	599,40	299,70	2,37	3,35
Experimental Error	27,00	3410,10	126,30		
Total	29,00	4009,50	426,00		
INSIGNIFICANT MODEL					

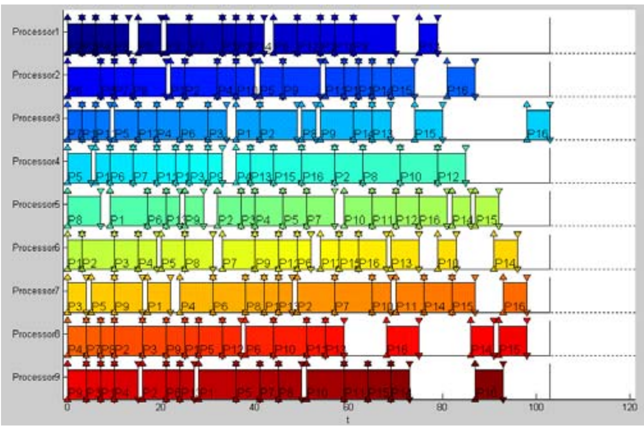

Figure 2. Makespan= 103. Idle Time= 227

Likewise, the problem taken under consideration was developed under two commercial programs, where best found results were 133 and 123 respectively, measured in makespan variable and, 497 and 407 respectively, that correspond to the total idle time variable, as illustrated in the following GANT chart (Figures 3 and 5).

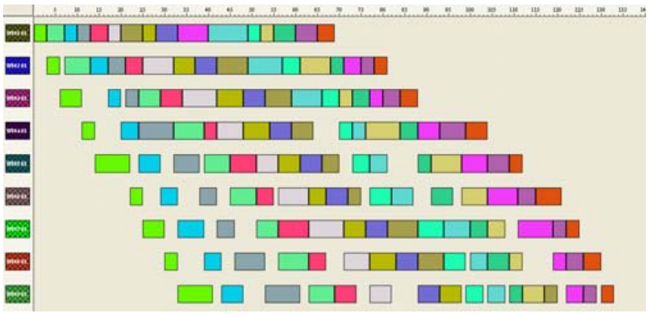

Figure 3. Commercial software solution 1. Makespan = 133. Idle Time= 497. General Heuristics Problem.

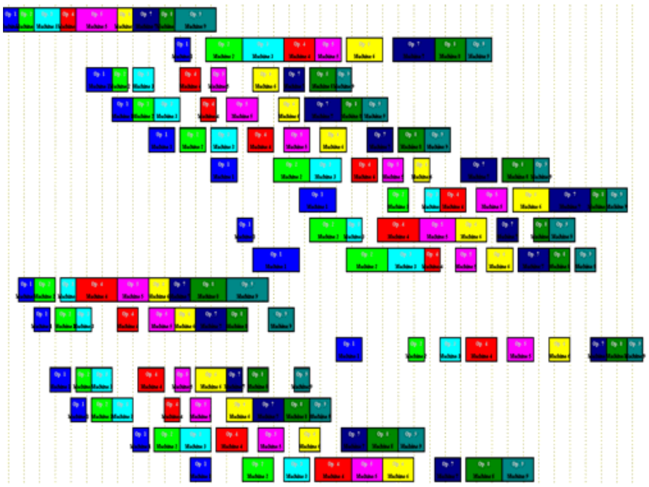

Figure 4. Commercial software solution 2. Makespan = 123. Idle Time= 407. Heuristics Problem.

In addition, Table 5 results regarding Figure 1, show that the proposed methodology has an effectiveness of 92.95% and 73.88%, regarding makespan and total idle time variables. This last aspect, contrast with some commercial programs based on Expert Systems, where the highest effectiveness found was 74.43% and 80.48% respectively, measures in total makespan; and 38.43% and 46.92% respectively, measures in total idle time variable.

With this paper is expected to motivate the use of artificial intelligence techniques (Expert System) in low developed countries, where its production systems are manual, with short competitive levels

Results illustrated in this section (Table 5) show Expert Systems effectiveness and its solutions consistency, in the production sequencing processes, establishing this way a referent which, as expressed previously, will allow motivating artificial intelligence usage in enterprises. Specially, in low developed countries, where products systems have a large number of manual operations, which prevent them from reaching high competitive levels with world class standards.

5. Conclusions

As deduced from the variance analysis, different solutions found by means of these artificial intelligence techniques show that, regarding makespan and idle time, there are no significant differences between found results, in the different algorithm repetitions based on an Expert System.

Hence, this technique permits finding solutions with an approximation to the optimal of 92.95% and 73.88% in the considered variables.

Similarly, it is important to highlight that, compared to other techniques used by divers commercial programs, the proposed methodology in this paper showed greater effectiveness, because the commercial program results were superseded in 18.52% and 26.96% respectively, measured in makespan and total idle time process variables.

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