SHOP ORDERS SCHEDULING: DISPATCHING RULES AND GENETIC ALGORITHMS BASED APPROACHES

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ABSTRACT
In the wide context of production planning a critical role is played by the operative programming, or short period production planning, whose results affect considerably the production system performances. The research work presented in this paper is focused on the Shop Orders scheduling problem into a real manufacturing system using dispatching rules and genetic algorithms based approaches supported by Modelling & Simulation. The objective is to verify the behaviour of different dispatching rules as well as to test the potentialities of production planning guidelines obtained by using genetic algorithms.

Keywords: Manufacturing Systems, Production Planning, Shop Order Scheduling, Modeling & Simulation, Genetic Algorithms

1. INTRODUCTION

As well known the Shop Orders (S.O.s) scheduling problem within manufacturing systems is usually characterized by high complexity due to the different interacting variables and to the stochastic nature of the system itself (i.e. stochastic process and set-up times, stochastic lead times, etc.). In addition a real manufacturing process is characterized by a number of peculiarities such as machines unavailability (due to failures) machines duplications, S.Os contemporarily worked on more machines, priority S.Os, limited capacity of the intermediate buffers between machines, significant transportation times. The representation of the mentioned aspects by means of analytical models is an exceeding difficult task. In effect the analytical models representing such type of systems are usually characterized by restrictive assumptions. Note that analytical models characterized by restrictive assumptions allow to gain confidence about the S.Os scheduling problem even if they often fall short of results applicability.

One of the most widely used approach for studying scheduling problems within manufacturing systems is the Modeling & Simulation (M&S) approach that gives the possibility to take into consideration the high complexity of a manufacturing system avoiding restrictive assumptions and transferring on the real system the results obtained by using simulation models. Note that also a simulation model usually contains restrictive assumptions. However such assumptions usually aim at defining the physical and logical boundaries of the simulation model (i.e. modeling the inventory management system in a S.Os scheduling problem may not be necessary). In other words all the assumptions made in a simulation model allow to recreate a model that should be valid in its domain of applicability (the Verification, Validation and Accreditation assess the capability of a simulation model to represent a real system with satisfactory accuracy).

The S.Os scheduling activities within a manufacturing system are usually part of the production planning process. In turn the production planning process schedules all the production activities over different period of time: in the long period the planning aims at evaluating the quantity to be produced for each product and the production resources to be used; in the short period the objective is the optimal scheduling of the S.Os on the available machines.

In this paper we developed a simulation model of a real manufacturing system and we studies the S.Os scheduling problem by using both some classical dispatching rules and the genetic algorithms in order to find out specific scheduling guidelines to be used for improving manufacturing system performances.

Before getting into details of the research work let us give a brief summary of the paper. Section 2 describes the manufacturing process being analyzed in this paper. Section 3 proposes the manufacturing process modeling (simulation model development and simulation model verification, validation). Section 4 presents the simulation results. Finally the last section reports the conclusions and the research activities still on going.

2. THE MANUFACTURING PROCESS

The research work has been done in collaboration with a manufacturing system producing small metallic carpentry structures. Due to the high number of different structures the company top management decided to carry out a study devote to improve the efficiency of the short period production planning. In effect such need comes out from the continuous delays in S.Os completion that, in turn, cause the decrease of the customers' satisfaction level. To well understand all the steps of the research work, it is useful to give a brief description of the manufacturing process.

The manufacturing process has to be regarded as a flow shop system in which each S.O. has the same routing, thus the visiting order of the machines is always the same. The main manufacturing operations are described as follows:

- raw materials preparation (ID 1);
- cutting (ID 2);
- drilling (ID 3);
- welding (ID 4);
- assembly (ID 5);
- sandblast (ID 6);
- painting and drying (ID 7).

During the preparation phase all the materials, needed for each Shop Order are taken from the raw materials warehouse. The first operation of the manufacturing process is the cut performed by using a pantograph supported by laser cutting system and equipped for receiving CAM information (*Computer Aided Manufacturing*) directly from the production planning office. All the metallic components are then drilled in order to create all the holes needed for the assembly process. The main components are welding by using two types of welding technologies: MIG/MAG (Gas Metal Arc Welding) and TIG (Gas Tungsten Arc Welding). Thanks to the assembly process all the components are assembled and form the final metallic carpentry structure. The sandblast operation aims at cleaning the metallic surfaces (by using high speed particles that hit the surfaces) before the painting. Finally painting and drying activities complete the manufacturing process.

3. MODELING THE MANUFACTURING PROCESS

Two types of S.O. can enter the system: normal and priority. Usually normal S.Os are scheduled on a 2-weeks time window (each new S.O. enters in the last position of the 2-weeks queue). On the contrary, a priority S.O. can enter the 2-weeks queue in any position at any time (it depends on the priority level of the S.O.). In other words the system allows the *passing* between jobs. Each S.O. has a finite number *m* of operations, one on each machine and it is allowed to work twice a job on the same machine. All the S.Os entered into the system have to be necessarily completed.

Machines could not be available during the scheduling period because of the failures. Failures have been modeled by using a negative exponential distribution for both the Mean Time To Failure (MTTF, expressing the time between two consecutive machine failures) and the Mean Time To Repair (MTTR, expressing the time required for repairing the machine). Finally process and set-up's time are considered as stochastic variables each one with a specific statistical distribution. According to these hypotheses it follows that the case analysed belong to the *dynamic-stochastic* scheduling problem because new S.Os arrive during the scheduling horizon and most of the numerical quantities are stochastic.

The main steps of the simulation model development can be summarized as follows:

- data collection and distributions fitting;
- simulation model implementation;
- simulation model verification and validation.

3.1. Data Collection and Distribution fitting

The most important information were collected by means of interview and by using the company informative system. Data collected regard bill of materials, S.Os routing, S.Os inter-arrival times, number of S.Os for each customer, inventory control policies and suppliers lead times, process and set-up times, machines downtimes and uptimes, material handling modes and times.

All the stochastic variables have been analyzed in order to find out statistical distributions capable of fitting the empirical data with satisfactory accuracy. Figure 1 shows the histogram and the statistical distribution of the process time of the assembly operation. Figure 2 shows the histogram and the statistical distribution of the process time of the drilling operation.

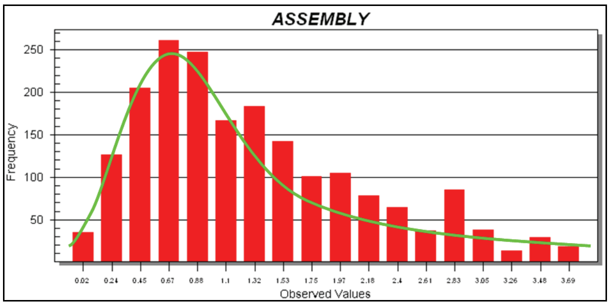

Figure 1: Histogram and Statistical Distribution of the Process Time of the Assembly Operation

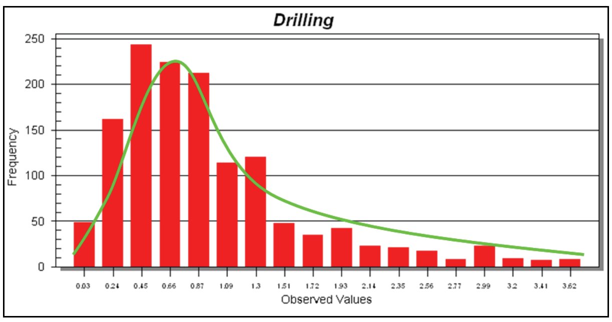

Figure 2: Histogram and Statistical Distribution of the Process Time of the Drilling Operation

3.2. The simulation model development

The simulation model was developed by using the discrete event simulation software eM-Plant by Tecnomatix Technologies. The main idea was to develop a flexible and time efficient simulator. A flexible simulator should be capable of easily integrating additional features as the time goes by; a time efficient simulator should require few time for executing simulation run.

Note that the simulator flexibility cannot be easily achieved if library objects are used for developing the simulator architecture. In effect each library object should represent a specific component/part of a real system; sometime such objects do not represent the real system with satisfactory accuracy. The solution to this problem is the simulator development by using programming code. eM-Plant provide the users with a simulation language (Simple++) that can be used for implementing classes and objects. Such classes can be accessed and modified at any time (also saved and used in other simulation models) assuring, as a consequence, high level of flexibility in terms of both model accuracy and future changes.

Concerning the computational efficiency of the simulator and the time required for executing simulation runs, we should take into consideration how a discrete event simulation software works. In a discrete event system the state of the system changes at discrete event time points due to the flow of entities inside the system (i.e. end of an operation, arrival of a new shop order, etc.). In other words entities take actions that change the state of the system. Usually entities are defined as classes instantiated inside the simulation model. Each entity can also have attributes used for storing specific information. Note that the higher is the number of entities flowing in the simulation model the higher is the computational load of the simulator. Consider the case of a manufacturing process in which thousands of components and products usually flow inside the system (it means thousands of entities flowing inside the simulation model). The approach used for developing the simulation model proposed in this paper is based on the idea to substitute the flow of entities with a flow of information opportunely stored in tables. The events generation is committed to specific objects (provided by the eM-Plant library) called event generators.

The change of the state of the system, due to the generation of an event, is managed by ad-hoc programmed routines; the programming code also takes care of updating all the information stored in the tables.

By following this approach, two main advantages can be obtained: (i) a great gain in term of computational load of the simulator; (ii) reduction of the time required for executing simulation runs. Figure 3 shows an example of information stored in table for each entity (shop order) flowing into the simulator.

The simulator main frame is called *model*. It contains 9 secondary frames. Each frame is built to recreate a specific operation of the real manufacturing system. In particular 7 frames recreate the operations described in section 2 (raw materials preparation, cutting, drilling, welding, assembly, sandblast, painting and drying) whilst the remaining 2 frames are respectively the *Production Manager* (PM) and the *Graphic User Interface* (GUI). The PM generates the S.Os and the relative production planning, takes care of S.Os scheduling, resource allocation and inventory management. The graphic user interface provides the user with many commands as, for instance, simulation run length, start, stop and reset buttons and a Boolean control for the random number generator (to reproduce the same experiment conditions in correspondence of different operative scenarios). Furthermore the GUI allows the user to select the dispatching rule to be used for S.Os scheduling or to select S.Os scheduling based on the results of genetic algorithms.

Let us introduce now the performance indexes implemented in the simulation model used for evaluating the goodness of the S.Os scheduling. We propose a multi measure approach based on orders completion time and on due dates. In particular the simulator monitors for each S.O. the following performance measures: the average and the variance of the *Flow Time* (FT), the average and the variance of the *Latiness* (LT) and the *Fill Rate* (FR). The FT of the *i-th* S.O. is the difference between the S.O. Completion Time (CT) and the S.O. Release Time (RT) as reported in equation 1.

$$FT_i = CT_i - RT_i \tag{1}$$

ID Shop Order	ID Customer	ID Item	Quantity	S.O. Routing	Bill of Materials	S.O. date of entry
1001	5895	EH04	12.00	table51	table61	2005/01/24 00:00:00.0000
1002	5895	EH01	10.00	table52	table62	2005/01/24 00:00:00.0000
1003	2008	EH01	10.00	table53	table63	2005/01/24 00:00:00.0000
1004	2576	EH01	10.00	table54	table64	2005/01/24 00:00:00.0000
1005	5895	EH02	2.00	table55	table65	2005/01/24 00:00:00.0000
1006	5895	EH01	6.00	table56	table66	2005/01/24 00:00:00.0000
1007	5895	EH03	10.00	table57	table67	2005/01/24 00:00:00.0000
1008	5895	EH02	2.00	table58	table68	2005/01/24 00:00:00.0000
1009	5895	EH03	20.00	table59	table69	2005/01/24 00:00:00.0000
1010	5895	EH03	10.00	table510	table610	2005/01/24 00:00:00.0000
1011	5895	EH03	6.00	table511	table611	2005/01/24 00:00:00.0000
1012	5895	EH04	6.00	table512	table612	2005/01/24 00:00:00.0000
1013	5895	EH02	20.00	table513	table613	2005/01/24 00:00:00.0000
1014	5895	EH04	30.00	table514	table614	2005/01/24 00:00:00.0000
1015	5895	EH02	20.00	table515	table615	2005/01/24 00:00:00.0000
1016	5022	EH03	36.00	table516	table616	2005/01/24 00:00:00.0000

Figure 3: An example of information stored in table for each entity (shop order) flowing into the simulator

The LT of the *i-th* S.O. is the difference between the S.O. Completion Time and the S.O. Due Date (DD), as expressed by equation 2.

$$FT_i = CT_i - DD_i \tag{2}$$

Finally the FR is the percentage of S.Os meeting the due date as expressed by equation 3.

$$FR_i = \frac{\sum_{i=!}^{k} S.O._i}{\sum_{i=1}^{n} S.O._i} \tag{3}$$

3.3. Simulation model Verification and Validation

The accuracy and the quality throughout a simulation study are assessed by conducting verification and validation processes (Balci 1998). Usually a real world system is abstracted by a conceptual model; in turn a conceptual model is then translated into a computerized simulation model. The verification aims at determining if the computerized simulation is an accurate translation of the initial conceptual model. A simulator must substitute the real system for the purpose of experimentation; to this end the simulator has to represent the real system with satisfactory accuracy. The level of accuracy is usually evaluated by the validation phase. For further details on simulation model Verification & Validation, refer to the American Department of Defence Directive 5000.59.

The simulator verification has been carried out by using the *Assertion Checking* dynamic technique. Such technique aims at checking what is happening inside the simulator against what we assume happening (further information in Adrion et al. 1982). In case of checking discordance, the technique reveals an error usually due to incorrect programming code or values. To detect errors inside the simulator we inserted global, region and local assertion in order to verify the entire model. A number of different errors were identified by the assertions and successively corrected (i.e. errors on S.O. routing, on machines set-up times, on raw materials inventory management, etc.

The simulator validation has been carried out by using the Mean Square Pure Error analysis (MSPE). The MSPE aims at evaluating the length of the simulation run that guarantees the goodness of the statistical results in output from the simulation model.

Considering the stochastic distributions implemented in the simulation model we can assert that the outputs of the simulation model are subjected to an experimental error with normal distribution, N(0, σ^2). The best estimator of σ^2 is the mean squares error. The simulation run has to be long enough to have small values of the MSpE of the performance measures being considered. In other words, the experimental error must not "cover" the simulation results. Considering the Flow Time, we can write:

$$MSpE(t) = \sum_{h=1}^{n} \frac{(FT_h(t) - \overline{FT}(t))}{n-1} \tag{4}$$

- $FT_h(t)$, value of the Flow Time at instant of time *t* during the replication *h*;
- $h=1,\dots,n$ number of replications.

Analogous equation can be written for the LT and the FR. The simulation run length chosen is 200 days. Such time, evaluated with four replications, assures a negligible mean squares error for the Flow Time. The same analysis for the Lateness and the Fill Rate gives lower simulation run lengths.

3.4. Genetic Algorithms implementation to support Shop Order scheduling

Once tested the validity of the simulation model, further implementations were carried out to introduce Genetic Algorithms (GA) as support tool for short period production planning. The GA was implemented as functional part of a particular tool called optimizer. This object aims at:

- optimising S.Os scheduling by means of GA;
- testing the proposed scheduling;
- monitoring the manufacturing system performances by using the Flow Time, the Lateness and the Fill Rate indexes.

It is important to highlight the nature of problem which must be solved by the optimizer and, of course, understand how it works. The problems concerning the stochastic shop orders scheduling cannot be solved only by means of simulation tools. In effect, after establishing a certain S.Os scheduling a simulation model can only evaluates the system performance under the scheduling proposed. By proposing a new S.Os scheduling, the initial solution can be improved or worsened. To improve the S.Os scheduling it is therefore necessary to use optimization algorithms which, thanks to an interface with the simulation model, find out the most suitable solution optimizing the scalar function chosen to measure scheduling goodness (i.e. the Flow Time). Optimization algorithms must find out acceptable solutions, while the simulation model must test, validate and choose the best solutions.

The interface between the simulation model and genetic algorithms was created through the programming of specific sub-routines, written using the simulation language Simple++. The use of genetic algorithms goes through three fundamental steps: (i) initial S.Os scheduling (proposed by the user); (ii) setting of genetic operators and algorithms initialization (iii) optimization.

4. SIMULATION RESULTS AND ANALYSIS

The research work focalizes on the Shop Orders scheduling problem into a real manufacturing system using dispatching rules and genetic algorithms based

approaches supported by Modelling & Simulation. The objective is to verify the behaviour of different dispatching rules as well as to test the potentialities of production planning guidelines obtained by using genetic algorithms.
The scheduling rules (implemented in the simulator) being tested in the following analysis are: (i) the Shortest Production Time (SPT); (ii) the Due Date (DD); (iii) the Longest Production Time (LPT).
Table 1 reports the average values of the FT, LT and FR in correspondence of each scheduling rule. The best performance in terms of flow time is guaranteed by the SPT rule, while the best performance in terms of LT and FR is guaranteed by the DD rule. Table 2 reports the standard deviation values for each performance measure in correspondence of each scheduling rule.

Table 1: Shop Orders Scheduling Rules and average values of the Performance Measures

	Flow Time (FT) [days]	Lateness (LT) [days]	Fill Rate (FR) [%]
SPT	4.1	1.7	87.38
DD	4.8	1.2	90.40
LPT	6.4	2.6	83.26

Table 2: Shop Orders Scheduling Rules and standard deviation of the Performance Measures

	Flow Time (FT) [days]	Lateness (LT) [days]	Fill Rate (FR) [%]
SPT	0.032	0.030	0.230
DD	0.041	0.033	0.190
LPT	0.037	0.036	0.210

Figure 4 shows the FT and the LT versus the scheduling rules. Note that the DD performs better in terms of respect of the due dates.

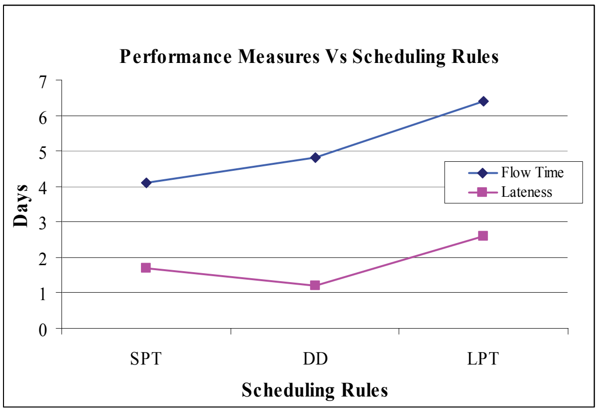

Figure 4: Performance Measures Vs Scheduling Rules

A number of simulation runs have been also made for investigating the S.Os scheduling by using the genetic algorithms. Three different optimizations have been carried out respectively trying to minimize the FT, minimize the LT and maximize the FR. Table 3 reports the simulated FT in correspondence of each generation; in particular for each generation the best value, the average value and the worst value are reported.

Table 3: Flow Time Optimization: Best Average and Worst Solutions found by GA

Generation	FT Best	FT Average	FT Worst
1	9.00	10.00	10.60
2	7.50	8.30	9.60
3	6.60	7.50	9.00
4	6.00	7.00	8.80
5	5.70	6.80	8.30
6	5.40	6.50	7.90
7	5.30	6.20	7.60
8	5.00	6.00	7.40
9	4.90	5.70	7.00
10	4.85	5.40	6.50
11	4.70	5.30	6.20
12	4.50	5.10	5.80
13	4.30	4.90	5.50
14	4.20	4.70	5.00
15	4.00	4.20	4.50
16	3.90	4.00	4.30
17	3.85	3.90	4.00
18	3.75	3.80	3.90
19	3.75	3.80	3.80
20	3.70	3.80	3.80
21	3.70	3.70	3.70
22	3.70	3.70	3.70
23	3.70	3.70	3.70

After 23 replications the best, the average and the worst solutions converge to the value 3.70 days. Note that such value is lower than best result obtained with the SPT rule (the improvement is about 9.8%). The figure 5 reports the performance graph that shows the FT optimization

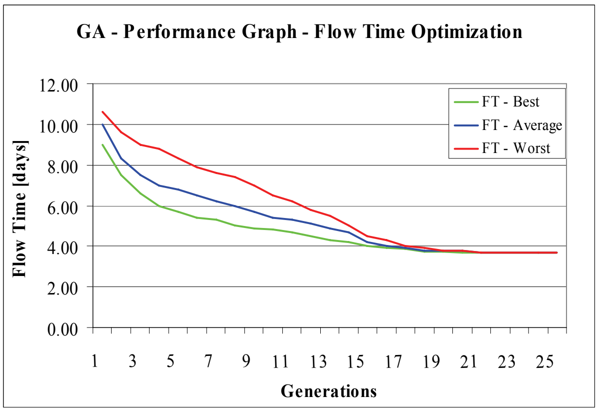

Figure 5: Flow Time Optimization

Analogously the table 4 reports the optimization results for the LT (best, average and worst values over 23 generations).

Table 4: Lateness Optimization: Best Average and Worst Solutions found by GA

Generation	LT Best	LT Average	LT Worst
1	4.25	5.05	6.05
2	3.75	4.65	5.45
3	3.25	4.35	5.05
4	3.00	3.95	4.85
5	2.85	3.75	4.70
6	2.65	3.50	4.45
7	2.50	3.30	4.25
8	2.25	3.05	4.00
9	2.00	2.85	3.70
10	1.85	2.75	3.50
11	1.75	2.60	3.25
12	1.65	2.35	3.00
13	1.50	2.05	2.90
14	1.40	1.85	2.65
15	1.30	1.60	2.35
16	1.30	1.40	2.05
17	1.20	1.30	1.75
18	1.15	1.25	1.50
19	1.10	1.15	1.40
20	1.10	1.15	1.30
21	1.05	1.10	1.20
22	1.05	1.10	1.20
23	1.05	1.05	1.10

After 23 replications the best, the average and the worst solutions converge to the value 1.05 days. Note that such value is lower than best result obtained with the DD rule (the improvement is about 12.5%). The figure 6 reports the performance graph that shows the LT optimization

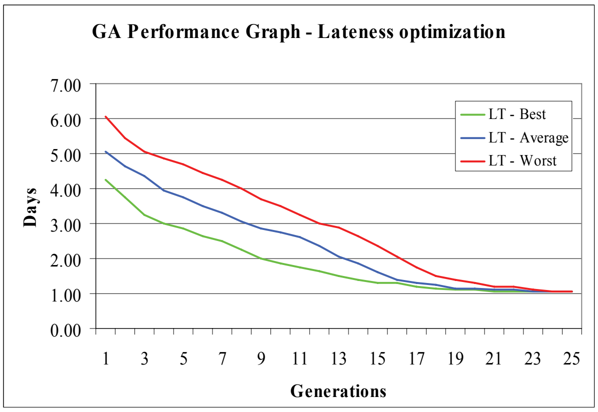

Figure 6: Lateness Optimization

Finally the table 5 reports the optimization results for the FR (best, average and worst values over 23 generations). After 23 replications the best, the average and the worst solutions converge to the value 95%. Note that such value is greater than the best result obtained with the DD rule (the improvement is about 4.6%). The figure 7 reports the performance graph that shows the FR optimization.

Table 5: Fill Rate Optimization: Best Average and Worst Solutions found by GA

Generation	FR Best	FR Average	FR Worst
1	81.25	79.00	78.00
2	82.33	80.70	79.10
3	83.10	81.50	80.20
4	84.20	82.25	81.00
5	85.00	83.30	81.90
6	85.80	84.40	82.70
7	86.70	85.50	83.90
8	87.90	86.50	84.10
9	89.00	87.70	85.50
10	90.05	89.00	86.70
11	90.88	89.65	87.90
12	91.56	90.32	89.00
13	92.21	91.15	89.90
14	92.78	91.99	90.50
15	93.50	92.10	91.40
16	93.75	93.00	92.10
17	94.00	93.50	92.80
18	94.25	93.80	93.20
19	94.35	94.20	93.80
20	94.50	94.40	94.15
21	94.77	94.60	94.45
22	95.00	94.90	94.80
23	95.00	95.00	95.00

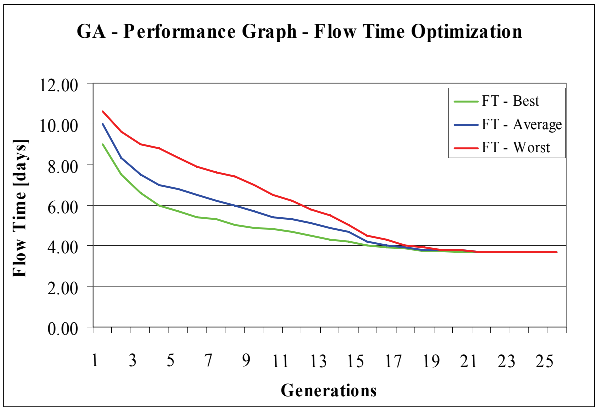

Figure 7: Fill Rate Performance Graph

5. CONCLUSIONS

The main goal of the research study was to verify the behaviour of different dispatching rules and the potential of genetic algorithms for the S.Os scheduling within a manufacturing system devoted to produce metallic carpentry structure. To this end the authors implemented a discrete simulation model by using an advanced modeling approach.

The analysis carried out show the behavior of three different scheduling rules in terms of Flow Time, Latiness and Fill Rate. In addition, three different optimizations have been made on the FT, LT and FR by using the genetic algorithms. The genetic algorithms are capable of finding better shop orders scheduling improving the results obtained by using the classical scheduling rule.

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