ON THE SHORT PERIOD PRODUCTION PLANNING IN INDUSTRIAL PLANTS: A REAL CASE STUDY

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ABSTRACT

Due to the increased level of competition, nowadays production systems have to keep high performances ensuring customer satisfaction, cost-reduction and high product quality. The features of the actual competitive scenario drive to pursue even higher levels of efficiency in companies management. In this perspective production planning, with special regard to short period production planning, plays a key role. As a matter of fact, while the long period planning aims at the evaluation of production quantities for each product, the short period planning aims at the definition of an optimal schedule to achieve even higher system performances. As well known a scheduling problem encompasses a great complexity, this kind of problem can be seen as a double allocation problem where the allocation of the jobs to production resources and the allocation of the jobs in a specific time production horizon have to be defined. The complexity grows even further considering that many interacting and variables must be taken into account simultaneously and the stochastic system behaviour cannot be neglected.

This paper faces scheduling problems in a real manufacturing system proposing an approach based on genetic algorithms, dispatching rules and Modelling & Simulation.

Keywords: Shop Order Scheduling, Discrete Event Simulation, Genetic algorithms, Dispatching Rules.

1. INTRODUCTION

The short period production planning tackles the problem of assigning the arriving jobs to workers, machines, equipment and other resources over time. As stated in (Kiran, 1998), scheduling problems are concerned with the determination of which resources should be used and the determination of the completion and starting time for each operation of each order so that no constraint are violated and some scalar functions, measuring the effectiveness of a particular schedule, are maximized (or minimized). Getting a lower inventory level, a high plant efficiency (it means high machine and labor utilization), and respecting due dates, are some examples of scheduling criteria.(Riane et al, 2001). The problems arising in production scheduling are notoriously very difficult and technically complex because they involve a large number of tasks and resources subject to different constraints and objectives; the complexity grows even further due to uncertainties in the manufacturing environment (Smith, 1992).

Note, in addition, that optimal allocation of the jobs to production resources over time is a combinatorial problem (Garey et al., 1976).

Scheduling problems can be formulated using analytical methods like mathematical programming or network theory. In this way , for small size problems, optimal solutions can be detected but, in most cases, the assumptions required for the analytical formulation are too restrictive so the resulting mathematical model may be not able to represent with accuracy the real problem (Son et al,1999). In other words theoretical notions tend to oversimplify crucial factors of the actual production process proving that an analytic formulation and resolution is inadequate.

Many research works on scheduling problems have been carried out with analytical approaches but most of them consider only one or few constraints (e.g. setups, failures, blocking, etc.) at the same time and as often as not one scheduling objective (criteria) while multiple scheduling objectives subject to several constraints have to be considered in real manufacturing systems. Also the enumerative methods and in general exact methods (usually applied when analytic procedures are not available) are prohibitive to use because of their unrealistic computing requirements (Riane et al, 2001).

It is evident that the advances of theory have had a limited impact in practice but it does not mean that advances in scheduling theory have been a waste of time because they have provided interesting insights into the scheduling problem (Pinedo, 2008). An alternative approach to face this problem lies in the use of Modeling & Simulation, simulating reality by building a simulation model (Johtela et al, 1997). Modeling & Simulation allows to overcome the gap between theory and real-world scheduling problems thanks to the capability to represent real word systems and its constraints (Frantzen et al, 2011).Different

simulation modeling approaches taken in the literature about job-shop have been reviewed by (Ramasesh, 1990)providing a state-of-the-art survey of the simulation-based research on dynamic job shop scheduling.
In the literature, there are two major approaches to deal with simulation-based scheduling problems, namely:

- A simulation-based approach using dispatching rules;
- A simulation-based approach using meta-heuristic search algorithms.

The first approach allows to put in comparison dispatching rules establishing which one performs better (Andersson et al, 2008) .
Carri (1986) describes this approach as the experimentation of scheduling rules and the assessment of the effect of different rules on shop's ability to meet delivery dates and utilize machines. Experimentation with simulation models makes it possible to compare alternative scheduling rules, test broad conjunctures about scheduling procedures and develop greater insight into the job shop operation (Vinod and Sridharan, 2011).
Many research works about this approach can be mentioned.
Parthanadeea and Buddhakulsomsirib (2010) develop a computer simulation for canned fruit industry and conduct computational experiment on the simulation model to determine a set of appropriate dispatching rules.
In Liu (1998) a two-stage simulation process has been presented: in the first stage, a number of dispatching rules are used as input parameters to generate candidate production schedules from a simulation model; in the second stage the performances of these production schedules are evaluated by another simulation model.
Goyal et al. (1995) have carried out a simulation study in order to analyze the scheduling rules for a flexible manufacturing system. Different combinations of scheduling rules have been applied evaluating their effect on system performances.
Huq and Huq (1995) have developed a simulation model, using a hypothetical hybrid job shop, to study the performance of different scheduling rules combinations with variations in arrival rates and processing times. Flow time, tardiness and throughput have been used as performance measures. They have found out that the rule combination performance varies with the performance criteria, and the combinations are sensitive to arrival rates and processing times.
Holthaus (1997) developed new scheduling rules by the combination of well known rules, and conducted a simulation-based analysis of those rules in the dynamic job shop environment. He concluded that the new scheduling rules are quite efficient.
Many other simulation studies have been carried out to evaluate the performances of dispatching rules: Holthaus and Rajendranb (1997),(Hicks and Pupong , 2006).
However, in general, this approach does not allow to find the optimal schedule.
The second approach mentioned above is based on the combined use of meta-heurist optimizer with simulation and allows to detect the optimal schedule (Andersson et al, 2008).
Among the meta-heuristic algorithms, genetic algorithms (GA) have been recognized as a general search strategy and an optimization method which is often useful for finding combined problems; for these reasons GA have been used with increasing frequency to address scheduling problems (Jeong et al, 2006).
The application of genetic algorithms to scheduling problem has been proposed by Bierwirth (1995), Syswerda (1991), Dorndorf and Pesch (1993), Yamada and Nakano (1992), Sakawa and Mori (1999) , Ghedjati (1999), Haibin and Wei (2001), Yun (2002), Vinod and Sridharan (2011) and many others.
The joint use of genetic algorithm and simulation are further proposed in Hou and Li (1991), Rabelo et al.,(1993), Ferrolho and Crisóstomo, (2007).
A comparison of these two approaches has been presented by Kim et al.,(2007) for job shop schedules of standard hydraulic cylinders and genetic algorithm were found to be better than dispatching rules (LPT, SPT, most work remaining MWKR, and least work remaining LWKR).
Similar results were found out in (Sankar et al., 2003) where the results obtained with GA are compared with the results obtained using six different dispatching rules including SPT, LPT, EDD, largest batch quantity (LBT), smallest batch quantity (SBQ) and highest penalty (HP). In this study it has been found out again that the solutions generated by GA outperform the solutions obtained by using Priority Dispatching Rules.
PDRs and meta-heuristic optimizer can also be jointly used with good results as shown by (Andersson et al, 2008)
In this research work we present a study in which simulation is jointly used with genetic algorithms and dispatching rules to face stochastic scheduling problems in a real manufacturing system. The main goal of the present work is to provide a useful tool that can be integrated in the management system of the company and that can be profitably and efficiently used for short period production planning. The paper is structured as follows: Section 1 presents an accurate description of the system under study, Section 2 presents the steps that have been followed to built the simulation model, Section 3 deals with the verification and validation of the simulator, in section 4 the main results have been presented and finally the last section describes the main conclusions .

2. MANIFACTURING PROCESS DESCRIPTION

The project has been developed in collaboration with a small company, which produces high pressure hoses, under specific request of the company top management.

During the initial meetings and analyzing the initial collected data it had been evident the efficiency eduction due to the short period production planning. In particular the effective production was smaller than the target production and there were continuous delays in Shop Orders (here in after S.O.s) completion that caused the decrease of the customers' satisfaction level. So the purpose of this study is to create a decision making tool (specifically a simulator) that could be easily integrated and profitably used in the company management system to support the short period production planning. It is useful to give a brief description of the manufacturing process in order to provide a greater understanding of the steps carried out in the present research work.

Each product (see figure 1) is made up by a high pressure hose, two adapters and two hydraulic fittings.

Fig. 1- Hydraulic hoses

The production process is made up by 8 operations:

- *Preparation* : all the materials, needed for each Shop Orders, are taken from the warehouse
- *Fittings stamp* : the information required by customers are stamped on the hydraulic fittings
- *Cut :* hydraulic hoses are cut in order to obtain the right hose length
- *Hose skinning:* the external (internal) hose diameter is reduced (increased) in order guarantee an optimal junction between hose, adapters and fittings.
- *Assembly*: hoses, fittings and adapters are assembled.
- *Junction*: all the components are definitively joined
- *Test :* hydraulic hoses are opportunely tested to check the resistance to high pressures
- *Final controls and packaging*

These operations are performed in the same order in which they are described but the cutting phase and the fittings stamp operation can take place in parallel since they involve two different components not yet assembled. Further for the cutting phase, two different machines are available: manual and automatic; these machines have different setup times and working times so different levels of productivity.

3. MODELING & SIMULATION FOR THE MANIFACTURING PROCESS

This research work faces a *dynamic-stochastic* scheduling problem. It is dynamic because new S.Os arrive during the scheduling horizon and the system allows the *passing* between jobs. Normal and priority S.Os can enter in the system. Usually normal S.Os are scheduled on a 2-weeks time window and each new S.O. enters in the last position of the queue. On the contrary, a priority S.O., depending on its priority level, can enter the 2-weeks queue in any position at any time-Each S.O. has a finite number *m* of operations, all the S.Os entered into the system have to be necessarily completed.

The stochastic nature of the problem is due to the presence of stochastic numerical quantities. In effect set-up's time can be considered as stochastic variables each one with a specific statistical distribution. Further, during the scheduling period, some failures can occur reducing the availability of machines. In the present work failures have been modeled by using a negative exponential distribution for both the Mean Time To Failure (MTTF) and the Mean Time To Repair (MTTR), where MTTF expresses the average time between two consecutive machine failures and MTTR expresses the average time required for repairing the machine.

Once the main features of the problem and the production process have been described, the main steps of the research work can be presented. The simulation model development can be summarized as follows:

- initial analysis, data collection and distribution fitting;
- simulation model development;
- Verification, Validation and Accreditation (VV&A);
- Genetic Algorithms implementation to support Shop Order scheduling,
- simulator integration in the company management system as real time decision tool for short period production planning .

All the phases for the simulation model development are detailed in the following sections.

3.1. Initial data analysis, data collection and distribution fitting

The most important information were collected by means of interview and by using the company informative system.

Data collection is concerned with information regarding products, working methods, short period production planning and management, actual S.O.s scheduling rules, inventory management and company informative system. In particular the collected data regard: customers, production mix, bill of materials, work shifts, process times, stocks and refurbishment times, due dates, frequency of customers requiring orders, frequency of customer orders, number of S.O. for each customers, quantity of pieces for each S.O.

The most important information were collected by means of interview and by using the company informative system. In particular a key role in data collection has been played by the company informative system from which a database has been extracted. The database reports information regarding final products as: operation identifying number, worker name, Shop Order identifying number , number of pieces, operation competition date, operation competition time, drawing identifying number, hose description, adapters and fittings description. In the same database are also reported information regarding final products opportunely ranked for due date and S.O. identifying number.
All the stochastic variables have been analyzed in order to find out statistical distributions capable of fitting the empirical data with satisfactory accuracy. Figure 2 shows the histogram obtained putting in relation the time process observed for the junction operation with the frequency of occurrence. The same kind of histogram has been built for each operation which makes up the production process.

Is then possible to find out the most suitable statistical distribution.

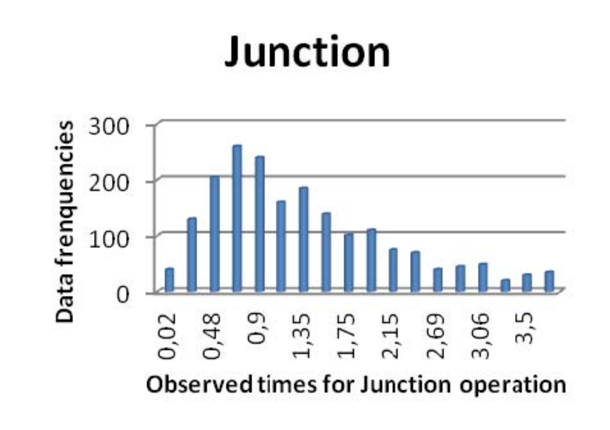

Fig 2: Histogram and Statistical Distribution of the Process Time for the Junction Operation

3.2. Simulation model development

Without doubt the most important step of a simulation study is the modeling phase. In this research work a new approach, quite different from traditional approaches, has been adopted; in the following there is a detailed description of the architecture used during the modeling phase.
The main requirement that has been taken into account was to develop a flexible and time efficient simulator. A flexible simulator is a simulator able to easily integrate new additional features over the time while a time efficient simulator is not time consuming in the execution of simulation run. So during the modeling phase we do not use the classic object oriented approach characterized by library objects and entities (that opportunely set and define the simulation model) but we propose a structural design completely based on programming code and tables to store the information.
In effect the simulator flexibility cannot be easily achieved by using library objects: each library object should represent a specific component/part of a real system but sometime such objects do not represent the real system with satisfactory accuracy. To overcome this problem a programming code must be used for the simulator development. In the present work classes and objects have been implemented by using Simple++ , a simulation language provided by eM-Plant. In this way classes can be accessed and modified at any time and also, if needed, used in other simulation models. So the use of a programming code in developing a simulation model ensures a great accuracy and offers the possibility to change it in the future according new emerging needs; as a consequence, high level of flexibility can be achieved.
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, for example at the end of an operation, at the arrival of a new shop order, etc. In other words entities with their actions change the state of the system. Usually entities are defined as classes instantiated inside the simulation model. So each entity can also have attributes in which specific information are stored. Note that the number of entities defined in a simulation model is strongly related to the computational load of a simulator: the higher is the number of entities flowing in the simulation model the higher is the computational load of the simulator. Consider that in most production processes thousands of components and products usually flow inside the system, it means thousands of entities flowing inside the simulation model and consequently a high computational load. To overcome this difficulty 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. Ad-hoc programmed routines manage the change of the state of the system due to the generation of an event; the information stored in the tables are updated by the programming code.
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 10 secondary frames (see figure 4).

In particular 8 frames are built to the recreate the operations described in section 2 (Preparation, Fittings stamp, Cut, Hose skinning , Assembly, Junction, Test, Final controls and packaging) whilst the remaining 2 frames are respectively:

ID CUSTOMER	ID SHOP ORDER	ID ITEM	S.O. ROUTING	QUANTITY	BILL OF MATERIALS	S.O DATE OF ENTRY
2008	2001	FG01	TABLE 18	50	TABLE 1	2011/05/01
5022	2002	FG02	TABLE 19	70	TABLE 2	2011/05/02
5895	2003	FG06	TABLE 20	90	TABLE 3	2011/05/03
1235	2004	FG07	TABLE 21	85	TABLE 4	2011/05/04
1568	2005	FG04	TABLE 22	60	TABLE 5	2011/05/05
5022	2006	FG03	TABLE 23	12	TABLE 6	2011/05/06
5022	2007	FG01	TABLE 24	165	TABLE 7	2011/05/07
5895	2008	FG09	TABLE 25	145	TABLE 8	2011/05/08
1235	2009	FG06	TABLE 26	12	TABLE 9	2011/05/09
2578	2010	FG08	TABLE 27	123	TABLE 10	2011/05/10
2578	2011	FG07	TABLE 28	145	TABLE 11	2011/05/11

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

- the *Production Manager* (PM);
- 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 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.

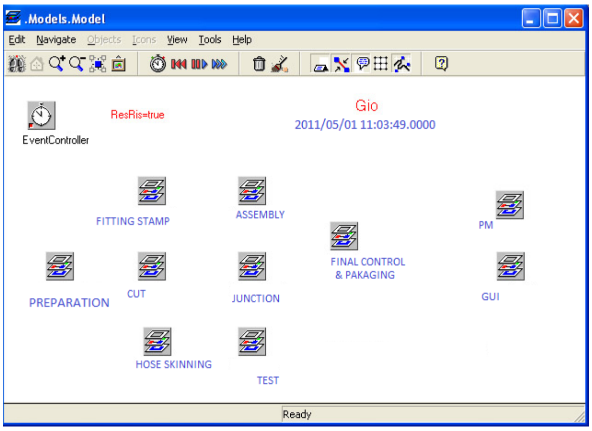

Fig. 4 – Simulator Main Frame

Furthermore the GUI 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. The dispatching rules that have been implemented in order to study the Shop Orders scheduling are the Short Production Time (SPT), the Longest Production Time (LPT), Due Date (DD). Some performances indexes have been implemented in the simulation model to evaluate the S.Os scheduling:

- the average and the variance of the *Flow Time* (FT),
- the average and the variance of the *Lateness* (LT),
- the *Fill Rate* (FR).

The FT of the *i-th* S.O., as reported in equation 1, is the difference between the S.O. Completion Time (CT) and the S.O. Release Time (RT).

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

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

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

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

3.3. Simulation model Verification , Validation and Accreditation

In the course of a simulation study the accuracy and the quality are not guaranteed “a priori”, for this reason the verification, validation and accreditation processes have to take place to assess the goodness of the developed simulation tool (Balci 1998). Usually a conceptual model is an abstract representation of a real system; in a simulation study the conceptual model is required to build a computerized simulation model. The verification allows to verify if the translation of the conceptual model into the computerized simulation model is accurate and correct. Furthermore the simulator has to be able to reproduce the behaviour of the real system with accuracy since it will take over from the real system for the purpose of experimentation. The validation phase is devoted to assess the accuracy of the simulation model. *Accreditation* is “the official certification that a model or simulation is acceptable for use for a specific purpose.” (DoD Directive 5000.59).

For further details on simulation model Verification, Validation & Accreditation, refer to the American Department of Defence Directive 5000.59.

There are two basic approaches for testing simulation software: static testing and dynamic testing (Fairley, 1976). In static testing the computer program is analyzed to determine if it is correct by using such techniques as structured walk-throughs, correctness proofs, and examining the structure properties of the program. (Sargent, 2000). Dynamic techniques require model execution and are intended for evaluating the model based on its execution behavior.(Balci 1997)

The simulator verification has been carried out by using the Assertion Checking dynamic technique. Detailed information about this technique can be found in Adrion et al. (1982). We inserted global region and local assertion in order to check the entire model. In this way some errors, most about raw materials inventory management, were detected and corrected. The simulator validation has been carried out by using the Mean Square Pure Error analysis (MSPE). The MSPE The MSPE is a typical technique devoted to find the optimal simulation run duration 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 $\sigma^2$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:

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

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

The accreditation analysis has been carried out in the present work by monitoring the performance indexes (FT and LT).

The best results in terms of mean daily flow time can be obtained using the Longest Production times scheduling rule (LPT). Taking into account that the model proposed in theory is too simplified, this result can be completely accepted even if it is in contrast with theory. Concerning the impact of the different scheduling rules on the mean daily lateness, the difference between the scheduling rules is not so remarkable.

3.4. Genetic Algorithms implementation to support Shop Order scheduling

The modeling architecture has been opportunely programmed to be interfaced with genetic algorithms. So 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 use of genetic algorithms goes through three fundamental steps:

- initial S.Os scheduling (proposed by the user);
- setting of genetic operators and algorithms initialization
- optimization.

The GA was implemented as a 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. In the following part the problem (which has to be solved) and the optimizer have been described. Simulation tool is not the only way to solve stochastic shop orders scheduling problems. A simulation tool allows to monitor the system performances under different S.Os scheduling but an optimization algorithm is required to improve the S.Os scheduling .

Interfacing the optimization algorithm with the simulation model it is possible to find out the most suitable solution (evaluated optimizing the scalar function chosen to measure scheduling goodness).

The interface between the simulation model and genetic algorithms was created through specific sub-routines written using the simulation language Simple++. In this way the optimization algorithms and the simulation model jointly work for the scheduling problem resolution: the former finds out acceptable solutions while the latter validates and chooses the best solutions.

4. SIMULATION RESULTS AND ANALYSIS

The research work faces the Shop Orders scheduling problem into a real manufacturing system devoted to hydraulic hoses production. The proposed approach is based on the use of Modelling & Simulation jointly used with dispatching rules and genetic algorithms. The system performances, under different dispatching rules have been tested, as well as the guidelines obtained by using genetic algorithms.

The scheduling rules (implemented in the simulator) being tested in the following analysis are:

- the Shortest Production Time (SPT);
- the Due Date (DD);
- the Longest Production Time (LPT).

The average values of the FT, LT and FR in correspondence of each scheduling rule are shown in Table 1. As it can be seen in table 1 the SPT rule guarantees the best performances in terms of Flow Time, while the DD rule allows to get the best performance in terms of lateness and Fill Rate. Table 2 reports the standard deviation values for each performance measure in correspondence of each scheduling rule.

		SPT	**DD**	**LPT**
Flow Time	**(FT) [days]**	3,600	4,580	5,590
Lateness	**(LT) [days]**	1,500	1,090	2,370
Fill Rate	**(FR) [%]**	78,640	79,250	73,780

Table 1: Average values of the Performance Measures

		SPT	**DD**	**LPT**
Flow Time	**(FT) [days]**	0,031	0,039	0,035
Lateness	**(LT) [days]**	0,028	0,031	0,036
Fill Rate	**(FR) [%]**	0,21	0,17	0,19

Table 2: Standard deviation of the Performance Measures for each Scheduling Rule

The S.Os scheduling has also been investigated by using genetic algorithms trying to minimize the FT, minimize the LT and maximize the FR. Table 3 reports the simulated FT in correspondence of each generation; for each generation are reported the best, the average and the worst FT values . After 25 replications the best, the average and the worst solutions converge to the value of 3.20 days. Note that such value is lower than best result obtained with the SPT rule (the improvement is about 9.17%). The optimization on the FT with genetic algorithms is also shown in the figure 5.

Generation	FT Best	FT Average	FT Worst
1	8,76	9,54	9,82
2	7,00	7,76	8,43
3	6,12	6,85	7,98
4	5,91	6,60	7,83
5	5,23	6,09	7,65
6	4,76	5,73	7,60
7	4,95	5,69	6,85
8	4,63	5,53	6,82
9	4,48	5,01	6,12
10	4,32	4,99	5,96
11	4,30	4,80	5,58
12	4,10	4,73	5,51
13	4,02	4,49	5,20
14	3,73	4,17	4,55
15	3,64	3,96	4,17
16	3,64	3,92	4,25
17	3,48	3,87	4,00
18	3,48	3,29	3,38
19	3,35	3,29	3,29
20	3,27	3,29	3,29
21	3,27	3,20	3,20
22	3,27	3,20	3,20
23	3,27	3,20	3,20
24	3,27	3,20	3,20
25	3,20	3,20	3,20

Table 3: Best, Average and Worst values of Flow Time obtained by GA

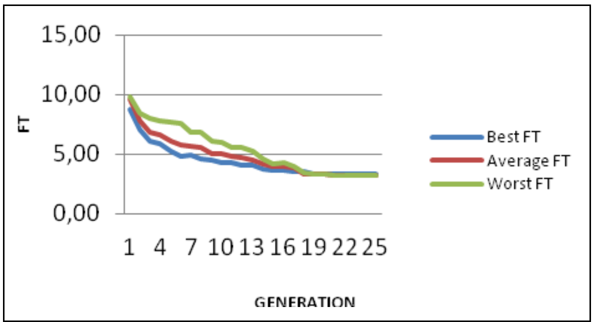

Fig 5: FT Optimization with Genetic Algorithms

The same approach has been applied for the Lateness optimization. The main results have been reported in table 4 and in figure 6. As in the previous case after 25 replications the best, the average and the worst solutions converge to 0.92 days. This value is still better than the result obtained with the DD dispatching rule, the improvement is about 16 % . Finally the table 5 and the figure 7 reports the optimization results for the FR. In this last case after 25 generations the algorithm converges with an improvement of about 1,4%.

Generation	LT Best	LT Average	LT Worst
1	3,85	4,25	5,61
2	3,78	4,03	5,49
3	3,62	3,95	4,99
4	3,46	3,82	4,67
5	3,19	3,67	4,28
6	2,92	3,46	4,05
7	2,68	3,24	3,91
8	2,20	2,97	3,72
9	2,05	2,86	3,35
10	1,90	2,51	3,27
11	1,79	2,12	3,16
12	1,65	2,07	3,06
13	1,49	2,00	2,94
14	1,26	1,83	2,29
15	1,19	1,64	2,03
16	1,13	1,48	1,82
17	1,09	1,29	1,76
18	1,02	1,14	1,58
19	0,99	1,03	1,32
20	0,95	1,00	1,20
21	0,92	0,99	1,14
22	0,92	0,95	0,99
23	0,92	0,92	0,92
24	0,92	0,92	0,92
25	0,92	0,92	0,92

Table 4: Best, Average and Worst values of Lateness obtained by GA

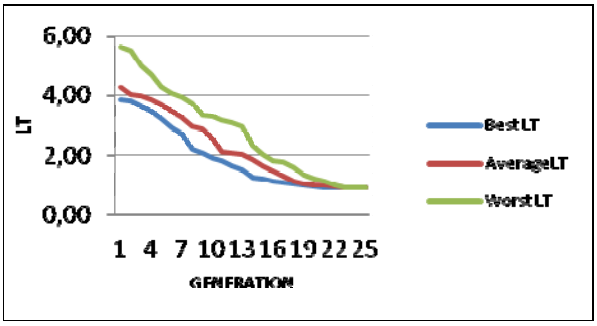

Fig. 6: LT Optimization with Genetic Algorithms

Generation	FR Best	FR Average	FR Worst
1	82,52	80,20	77,99
2	83,70	81,62	79,64
3	84,45	81,37	78,40
4	85,43	81,92	78,52
5	86,21	83,20	80,30
6	87,04	84,32	81,71
7	88,08	85,43	82,89
8	89,39	86,44	83,60
9	90,38	87,66	85,04
10	91,31	87,81	84,42
11	92,16	89,63	87,21
12	92,91	90,31	87,82
13	93,48	91,15	88,93
14	94,21	92,01	89,91
15	94,75	92,00	89,35
16	95,09	93,03	91,07
17	95,43	94,35	93,38
18	95,75	95,01	94,37
19	96,09	95,39	94,79
20	96,24	95,65	95,16
21	96,34	95,87	95,51
22	96,38	96,14	96,00
23	96,42	96,36	96,36
24	96,42	96,42	96,42
25	96,42	96,42	96,42

Table 5: Best, Average and Worst values of Fill Rate obtained by GA

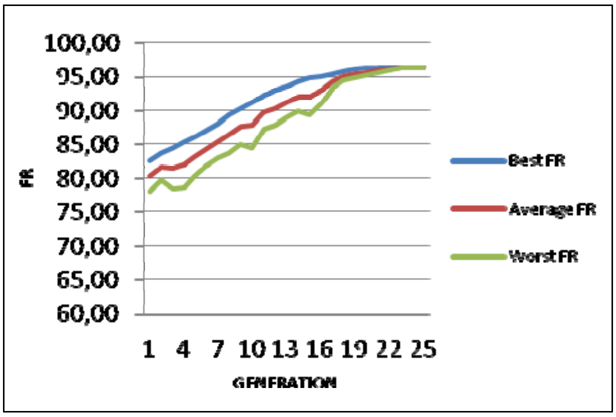

Fig. 7: Fill Rate Optimization with GA

5. CONCLUSIONS

The authors implemented a discrete simulation model by using an advanced modeling approach. The simulation model was developed with the purpose to study the behaviour of different dispatching rules and the potential of genetic algorithms for the S.Os scheduling within a manufacturing system devoted to produce hydraulic hoses. The simulator architecture is totally different from the traditional modeling approach proposed by the commercial discrete event simulation packages. Such architecture is completely based on a different modeling approach :

- all the objects have been modeled by means of code
- all the information have been stored in table;

These features allow to get high flexibility in terms of future changes and new tools implementation (for example genetic algorithms or neural network).
The behavior of three different scheduling rules was analyzed in terms of Flow Time, Lateness and Fill Rate. In addition, Genetic algorithms were also used to perform three different optimizations: FT, LT and FR . Comparing the results obtained in these two steps of the research work it was found out that the genetic algorithms are capable of finding better shop orders scheduling improving the results obtained by using the classical scheduling rule. Further, thanks to the high computational efficiency, the simulator has the potentials to be used real-time for short period production planning.
In conclusion, the approach proposed in this case study during the modeling phase has been useful for creating a decision and problem solving tool that can be profitably used by the integration in the company informative system and used real-time to support stochastic S.O.s scheduling.

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