Planeamento de Produção na Logoplaste Santa Iria

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Abstract

In this work, a production scheduling problem is developed through a Simulated Annealing approach, consisting of a mono-objective approach and a bi-objective approach with several objective functions including the Total Delay minimization, total production time minimization and makespan minimization. The algorithm is applied to a plastic container facility, which operates an injection molding process with several parallel machines. The algorithm applicability and its performance is illustrated through two production strategies, the make-to-order (MTO) and make-to-stock (MTS). In the latter inventory management is taken into account.

1 Introduction

Nowadays the uncertainty, competitiveness and globalization has huge impact on all manufactures facilities and their markets. The demand uncertainty triggers high prices variability not only in the final product but also in the raw materials. This environment prompts the performance improvement of all companies' process, in order to reduce their operating costs. On the other hand, the new technologies and software developments allow sophisticated operations' management enhancing production capabilities and efficiency. Therefore companies are investing time and money on the development of customized information systems not only to manage, plan and schedule its manufacturing process, but also control de inventory and its distribution.

When the process efficiency and productivity improvement is the goal, a support decision system to characterize an efficient scheduling in a reasonable time is very important.

Despite some research has already been made in this area using exact approaches, recently development have been also focused on meta-heuristics.

Chibeles-Martins *et al.* [1] developed Simulated Annealing methodology for the optimal design and scheduling of multipurpose batch plants and its comparison was made with the exact approach. The same authors [2], in the following year extended the previous work through the application of a multi-objective approach, and an efficient frontier characterization as a decision support tool was developed. Roshanaei *et al.* [3] developed a methodology for the flexible job shop scheduling problem through a SA algorithm, for large instances. Jia *et al.* [4] considered a more generic scheduling algorithm, for *n* jobs, with variable lots dimensions, using *m* identical and parallel batch machines, in order to minimize the makespan. Shivasankaran *et al.* [5] developed a hybrid sorting immune simulated annealing technique for solving a multi-objective flexible job-shop scheduling problem.

In this paper a Simulated Annealing algorithm is developed for an injection molding process schedule. The algorithm performance is illustrated in a real case study through the characterization of two process strategies and its statistical results analysed.

2 Modelling Framework

The meta-heuristic approach developed in this work in based in the Simulated Annealing algorithm proposed by Kirkpatrick *et al*. [6] and Cerny *et al*. [7]. However some adaptations must be done to improve the algorithm's efficiency and effectiveness. These adaptations take into account the problem characteristics under study.

Simulated Annealing can be classified as a Local Search Meta-Heuristic. It can be initialized with a constructive heuristic and improved iteratively. For each iteration the algorithm selects a solution from the current neighborhood. In order to prevent the algorithm early stop on a local optimum, a mechanism based on the Metropolis Algorithm was incorporated, as well as the tuning of some parameters was undertaken, to guarantee efficiency and effectiveness. The parameters tuning

are performed in: initial temperature (*T*), cooling schedule (*R*), Number of iterations at each temperature level (*NIST*) and stop criterion.
Other features are tailored based, such as:

- Objective function
- Initial solution generation
- Neighborhood function

2.1 Mono-Objective Approach

The mono-objective's algorithm procedure characterization, denominated by MonoSA, is shown in **Error! Reference source not found.**. The MonoSA first sub-procedure (I) defines the initial solution generation. The second (II) addresses the neighbor solution, followed by the third sub-procedure (III) which deals with the new solution acceptance. The fourth (IV) analyzes the neighbor solution efficiency and, finally, the stop criterion and the restart mechanism are controlled by sub-procedure V.
Sub-Procedure I: The initialization of the SA parameters and generation of the initial solution for the algorithm to start is developed.
The initialization is made by feeding the algorithm with all the data and parameters, such as: number of products (P), machines (M) and orders (O), setups and processing times.
The initialization solution is obtained through the following steps:

1. Select the first order;
2. Select the machine with the lowest completion time;
3. Assign the order to the machine selected in step 2;
4. Go to step 2 until all the machines are selected, otherwise go to step 5;
5. Generate the orders' completion times by considering the setup times;
6. Compute the delay of each order. If the order is on time the delay is 0, otherwise the delay is considered;
7. The objective function is computed;

This sub-procedure concludes by setting the initial solution as the algorithm current solution.

Sub-Procedure II: this sub-procedure explores the search space, using the initial solution the temperature (T_1) is updated, through the classical geometric cooling mechanism. The temperature is periodically reduced from a relatively high value to near zero using Equation (1), as cooling schedule scheme.
Each temperature level (T_k) is maintained through a number of iterations ($NIST_1$).

$$T_{k+1} = RT_k \quad (1)$$

A neighbor solution is defined through a current solution movement. In this work is developed two types of movements. One movement exchanges the orders between different machines, while the other exchanges consecutive orders on a machine's line-up.
The second sub-procedure concludes with a new solution (s'_i) characterization.

Sub-Procedure III: this sub-procedure evaluates the new solution quality and its acceptance is analyzed.
If the neighbor solution (s'_i) has a better objective function value ($f_1(s'_i)$) then the new solution is automatically accepted, otherwise is accepted according to the acceptance probability, P_{ac}, defined in Equation (2), from Kirkpatrick *et al.* (1983)

$$P_{ac} = \begin{cases} 1 & f_1(s'_i) > f_1(s_i) \\ e^{\frac{f_1(s'_i) - f_1(s_i)}{T_1}} & otherwise \end{cases} \quad (2)$$

Escaping from local optimum by accepting lower quality solutions is critical in SA. This probability decreases with the temperature's decrement as the method progresses. The acceptance probability also depends on the difference between objective function values. High differences lead to lower probabilities at the same temperature level.

Sub-Procedure IV: this sub-procedure analyzes if the current solution is better than the best solution so far, replacing it by the current solution, if necessary.

Fifth Sub-Procedure V: The length of the search is determined by the temperature, which starts with positive value and decreases as the search goes along, until the search is finally frozen.
In this work two stop criteria are used, the temperature lower than 0.00001 or the objective function *f(s$_i$)* reaches the zero value (zero-delay). The algorithm stops when one of the criteria is verified.

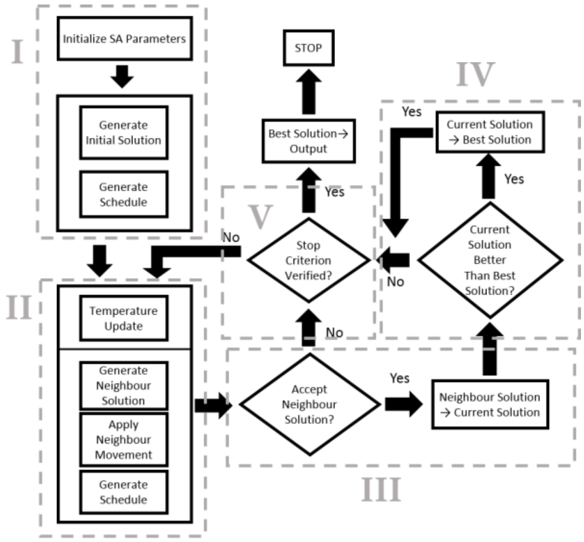

Figure 1 MonoSA algorithm characterization.

2.2 Bi-Objective Approach

The bi-objective's algorithm comprehends two different stages, the first one corresponds to the MonoSA algorithm and consists on the minimization of total delay while the second consists on the minimization of total production time or makespan. The procedures for the second stage are shown in Figure 2. The BiObSA first sub-procedure (I) resets the initial parameters values. The second (II) addresses the neighbor solution, followed by the third sub-procedure (III) which deals with the new solution acceptance. The fourth (IV) analyzes the neighbor solution efficiency and, finally, the stop criterion and the restart mechanism are controlled by sub-procedure V.
Sub-Procedure I: The algorithm's second stage starts with the best solution found in the first stage as the initial solution. This procedure comprehends the initialization of the second set of parameters values, temperature T_2, cooling rate R_2 and number of iterations at each temperature level $NIST_2$.

Sub-Procedure II: this sub-procedure comprehends the temperature update and the neighbor solution generation. The methodology used for the neighbor solution generation and for the temperature update are the same as the MonoSA, considering the second objective parameters T_2, R_2 and $NIST_2$.

Sub-Procedure III: this sub-procedure evaluates the new solution quality and its acceptance is analyzed. The procedure follows the same principle as MonobSA with the difference that in order to be accepted, a solution also requires zero-delay solution.

Sub-Procedure IV: this sub-procedure analyzes if the current solution is better than the best solution so far, replacing it by the current solution, if necessary.

Fifth Sub-Procedure V: In this stage the algorithm stops when the temperature reaches values lower than 0.00001.

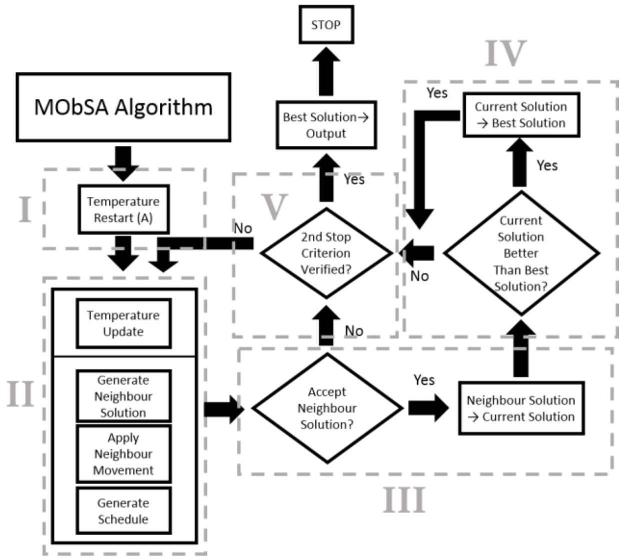

Figure 2 BiObSA algorithm characterization

3 Problem Characterization

Our case study focuses in a plastic containers facility. This type of industry operates under saturated markets with huge competitiveness levels and low unitary margins. The key factor for company's success is the final product price. Therefore cost minimization has a huge impact in its operations.
The facility under study receives weekly orders with different due dates to fulfil the customers demand, for the following week.
The production process is an injection molding characterized by several parallel machines and molds to produce containers as final products. Each container is characterized by two different parts, a bottom and a cover, with its own shape, label and color.
Every time a different containers order is put into production a set of changeover tasks, must be done. The changeover tasks must be performed every time a mold, dye or label must be changed, trigged by a new container characteristics. As an example, in some mold cases, several hours are required to conclude a changeover task. In this facility, the changeover time is not only product, but also machine complexity dependent and has a high impact in process productivity.
Nowadays, the facility operates under several limitations: for some products has high hand-on project inventory to overcome the demand uncertainty; a poor scheduling program neglecting products sequence and set-up time minimization, which is reflected in a high number of changeover tasks and customers' service level.
The aim of this work is to overcome the aforementioned limitation, enhancing not only the set-up minimization by reducing the number of changeover, but also developing an efficient production scheduling.

In total three objective function were studied, minimization of total delay, minimization of total production time and makespan minimization. These objective function were applied to mono and bi-objective algorithms in the following combinations:

1. Mono-objective algorithm for the minimization of total delay
2. Bi-objective algorithm for the minimization of total delay and total production time
3. Bi-objective algorithm for the minimization of total delay and makespan

4 Case Study

The aim of the proposed algorithms is to develop a scheduling of a plastic container facility to produce containers and fulfill weekly orders. Each container requires one bottom and one cover, and has its own characteristics, such as: shape, labels and colors. From now on a cover and a bottom are designated as products.
In the case under study 15 containers, equivalent to 30 products are produced, in 8 machines to fulfil 40 orders at the end of the week. An order is characterized by a product, a demand quantity and a due date. The processing and set-up time are machine and product dependent. For confidentiality reason, the process data are omitted.
To overcome some of the aforementioned limitations the algorithm performance is illustrated through two process strategies: the make-to-order (MTO) and the make-to-stock (MTS) strategy. The latter also considers inventory management.
In order to apply the algorithms, a parameters tuning was performed over the cooling rate (R), number of iteration at the same temperature level ($NIST$) and initial temperature (T). The cooling rate was analyzed over the values 0.95, 0.975 and 0.99, and the number iterations analyze over the values 100, 250 and 500. The initial temperature was selected empirically through several algorithm executions.
Regarding MonoSA the algorithm showed the best performance for T_1=500, $NIST_1$=250 and R_1=0.99 for both production strategies. The sets of parameters found for each of the BiObSA algorithms are shown below.

Make-To-Order strategy (T_1=500, $NIST_1$=250 and R_1=0.99):
Minimization of total production time - T_2=250, $NIST_2$=250 and R_2=0.99
Makespan minimization - T_3=1500, $NIST_3$=250 and R_3=0.99

Make-To-Stock strategy (T_1=500, $NIST_1$=250 and R_1=0.99):
Minimization of total production time - T_2=1000, $NIST_2$=250 and R_2=0.99
Makespan minimization - T_3=500, $NIST_3$=250 and R_3=0.99

4.1 Computational Results

In this paper the authors apply two strategies MTO and MTS to analyze the proposed algorithm performance using a Intel Core i7-3610QM, 2.30 GHz, 8 GB RAM.

4.1.1 Mono-Objective Approach (MObSA)

The algorithm performance is evaluated for the same set of orders and its results are shown in Figure 3 and 4, for MTO and MTS, respectively.
The objective function values show different behavior between the strategies. The algorithm applied to a MTO strategy initiates with a higher objective function values and requires more iterations to reach the zero-delay, when compared with the MTS. The MTS algorithm reaches the zero-delay at an early iteration for all the tested parameters values, 100, 250 and 500 for the number of iterations and the values 0.925, 0.975, 0.99 for the cooling rate.
The higher performance from MTS strategy is justified by considering simultaneously the process schedule and inventory management in the algorithm. The orders considered for production follows the first-in-first-out rule, after inventory availability analysis. If the facility has enough on-hand inventory, the order is totally satisfied right away, otherwise the current need are quantified and its consolidation is analyzed before a production task is scheduled. If the due date allows orders consolidation, not only the set-up but also the delay minimized is performed.
The objective function values distribution over time was also analyzed in both strategies, for 200 runs, with a cooling rate of 0.99 and 250 iterations at the same temperature level. As is shown in Figure 5, the MTO strategy reached the optimal value in 89% of the runs. The remaining runs shows delay values higher than a working day shift, suggesting that additional tuning is necessary. The average CPU time for a run was 7 seconds.
The objective function value distribution over time for strategy MTS is omitted since the algorithm found zero-delay solutions for all the executions performed. Nonetheless in the 200 runs the objective function converged to a zero-delay in an average of 0.1 seconds and visited an average of 2433 solutions until the best solution was found.

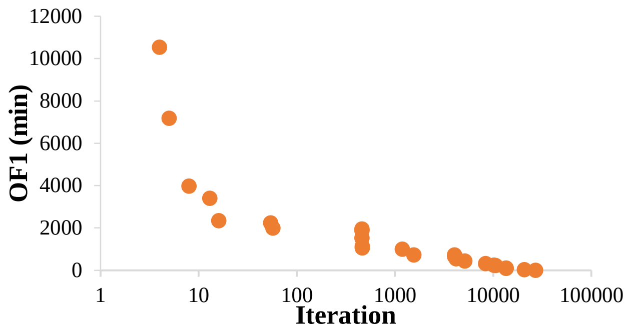

Figure 3 MTO objective function results evolution.

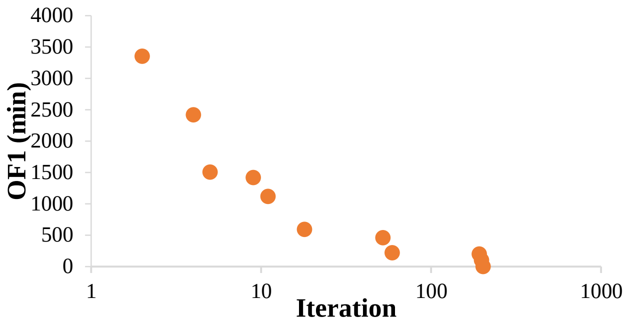

Figure 4 MTS objective function results evolution.

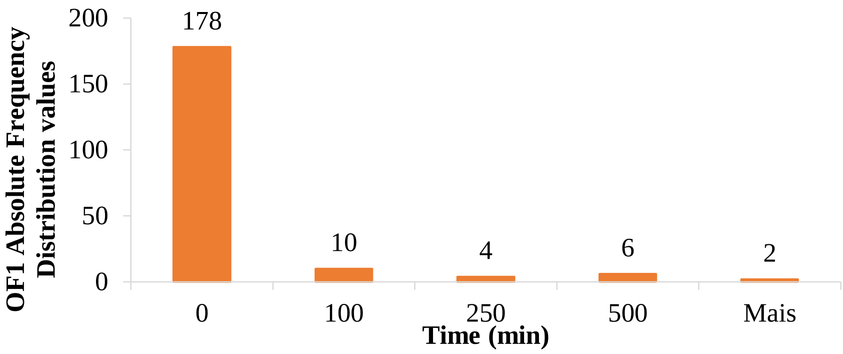

Figure 5 MTO objective function distribution values.

4.1.2 Bi-Objective Approach (BiObSA)

BiObSA algorithms can be separated into two different steps, the first step corresponds to the first objective function while the second corresponds to the second objective. For our case the first step always correspond to the minimization of total delay (MonoSA, OF_1) while the second step can be the minimization of total production time (OF_2) or the makespan minimization (OF_3). Therefore the parameters used for the first stage of the algorithms for both MTO and MTS strategies correspond to the parameters tuned for MonoSA of T_1=500, $NIST_1$=250 and R_1=0.99.

4.1.2.1 Make-To-Order Strategy (MTO)

The minimization of total production time (OF_2) over one execution with the tuned parameter values (T_2=250, $NIST_2$=250 and R_2=0.99) are presented in Figure 6. The OF_2 is reduced in 14% (1635 minutes, approx. 27.5 hours), from the starting zero-delay solution of 197.8 hours to 167.6 hours for the best solution found. This solution was obtained within 365 seconds (approx. 6 minutes).

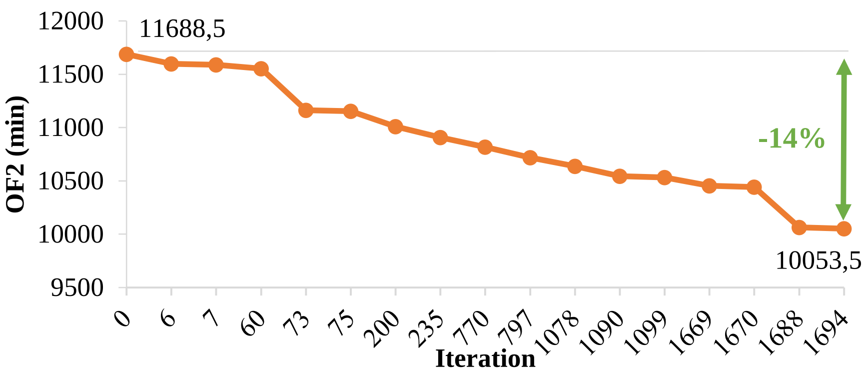

Figure 6 BiObSA MTO for minimization of total production time (OF2) evolution

The production plan for the minimization of total production time OF_2 is presented in Figure 7. Each machine has its own sequence of orders to produce resulting in different makespans and total setup times.
This production plan produces a total of 2540 minutes of setup time that is distributed between the 8 machines. Since OF_2 is considered the sum of all production time the algorithm tries to sequence all orders of the same product in the same machine (see products 1, 4, 6, 16, 17 and 21) if the corresponding due dates allow.
For this objective function the processing time of each machine is the main factor contributing to the orders' scheduling therefore it is noticed that the slower machines are scheduled with less orders (ex. machine 1 with 2 orders) while the faster machine are scheduled with more orders (ex. Machine 2 with 6 orders), causing longer makespans for the faster machines.

Mach.	1	2	3	4	5	6	7	8	9	Makespan	ST
M1	*O14, P15*	*O10, P11*								370	10
M2	*O6, P7*	*O9, P10*	*O11, P12*	*O13, P14*	*O12, P13*	*O39, P14*				2630	340
M3	*O2, P3*	*O38, P6*	*O5, P6*	*O8, P9*	*O7, P8*					1225	610
M4	*O15, P1*	*O32, P1*	*O34, P2*							1050	10
M5	*O1, P2*	*O4, P5*	*O3, P4*	*O36, P4*						1160	310
M6	*O19, P20*	*O26, P27*	*O35, P19*	*O20, P21*	*O37, P21*	*O18, P19*				1130	130
M7	*O25, P26*	*O22, P23*	*O24, P25*	*O21, P22*	*O23, P24*					848,5	600
M8	*O33, P17*	*O16, P17*	*O17, P18*	*O31, P16*	*O30, P16*	*O28, P29*	*O29, P30*	*O40, P29*	*O27, P28*	1640	530
OF1	0										
OF2	10053,5										
OF3	2630										
Total ST	2540										

Figure 7 BiObSA MTO for minimization of total production time (OF2) production plan

Regarding the makespan minimization (OF_3), the evolution for one execution with the selected parameter values (T_3=1500, $NIST_3$=250 and R_3=0.99) is presented in Figure 8. Results show a 14% reduction (305 minutes, approx. 5 hours) in the objective function from the starting zero-delay solution of 36.5 hours to 31.4 hours. This reduction highlights the importance of the second objective for optimizing the production scheduling at the factory since all machines will be available for new production orders 5 hours earlier with no delays.

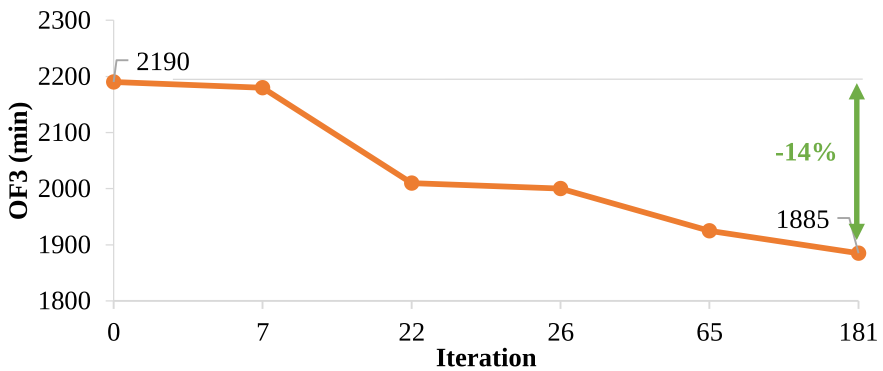

Figure 8 BiObSA MTO for makespan minimization (OF3) evolution

The production plan for this algorithm is presented in Figure 9. In this case, since the objective function shifts between the machines that have the longest makespan they do not minimize the makespan for the other machines. Consequently the setup time is not addressed for all machines resulting in a total setup time of 3690 minutes (approx. 61.5 hours). For the same reason the sequencing of orders of the same product is only important for the machines with the longest makespans resulting in longer setup times (see products 6, 17, 19, 21, and 29).

Regarding the scheduling sequence it is noticed that the orders are allocated more evenly between machines. For example machine 1 is the machine with the longest unitary production time. For the minimization of the previously studied OF_2 two orders are allocated to machine 1 while for the minimization of OF_3 three orders are allocated to machine 1. This increases the makespan in more than 1000 minutes in order to release production time in other machines (ex. machine 2).

Mach.	1	2	3	4	5	6	7	8	9	Makespan	ST
M1	O10, P11	O14, P15	O13, P14							1380	20
M2	O6, P7	O9, P10	O12, P13	O39, P14						1710	320
M3	O2, P3	O5, P6	O38, P6	O7, P8	O8, P9					1225	610
M4	O32, P1	O36, P4	O15, P1	O34, P2						1710	610
M5	O1, P2	O4, P5	O3, P4	O11, P12						1885	610
M6	O37, P21	O20, P21	O19, P20	O35, P19	O18, P19	O26, P27				1300	300
M7	O25, P26	O24, P25	O23, P24	O22, P23	O21, P22					758,5	510
M8	O30, P16	O17, P18	O16, P17	O33, P17	O31, P16	O29, P30	O27, P28	O40, P29	O28, P29	1820	710
OF1	0										
OF2	11788,5										
OF3	1885										
Total ST	3690										

Figure 9 BiObSA MTO for makespan minimization (OF3) production plan

4.1.2.2 Make-To-Order Strategy (MTO)

Regarding the minimization of total production time (OF_2), the evolution for one execution with the selected parameter values (T_2=1000, $NIST_2$=250 and R_2=0.99) shows a 19% reduction (2455 minutes, approx. 40.9 hours) in the objective function from the starting zero-delay solution of 218.2.8 hours to 177.3 hours. This solution was obtained within approx. 35 seconds. Results are presented in Figure 10.

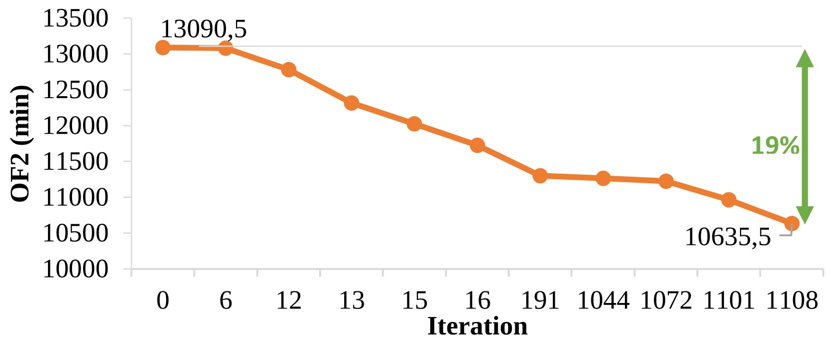

Figure 10 BiObSA MTS for minimization of total production time (OF2) evolution

For this algorithm the initial orders are aggregated by product. Therefore all production orders consist on different products. The production plan generated (see Figure 11) produced a total of 2180 minutes of machine setup time (approx. 36.6 hours) distributed between all 8 machines. For example machine 2 produced a total of 320 minutes of setup time that consists of one mould changeover (300 minutes) between product 2 and product 12 and two dye changeovers (2x10 minutes) between products 12, 13 and 14. For this machine the total production time is 2860 minutes (approx. 47.6 hours) for the 4 production orders scheduled.

Mach.	1	2	3	4	5	6	7	8	9	Makespan	ST
M1										0	0
M2	O2, P2	O12, P12	O13, P13	O14, P14						2860	320
M3	O3, P3	O6, P6	O8, P8	O9, P9						1510	610
M4	O10, P10	O7, P7	O4, P4	O5, P5						1570	320
M5	O1, P1									925	0
M6	O27, P27	O20, P20	O19, P19	O21, P21						1320	120
M7	O22, P22	O25, P25	O23, P23	O24, P24						730,5	300
M8	O18, P18	O17, P17	O16, P16	O29, P29	O28, P28					1720	510
OF1	0										
OF2	10965,5										
OF3	2860										
Total ST	2180										

Figure 11 BiObSA MTS for minimization of total production time (OF2) production plan

For the makespan minimization, the evolution of OF_3 for one execution with the selected parameter values (T_3=500, $NIST_3$=250 and R_3=0.99) is presented in Figure 12. Results show an 8.4% reduction (535 minutes, approx. 9 hours) in the objective function from the starting zero-delay solution of 35.7 hours to 28.8 hours. This reduction highlights the importance of the second objective for optimizing the production scheduling at the factory since all machines will be available for new production orders more than one working shift earlier (9 hours).

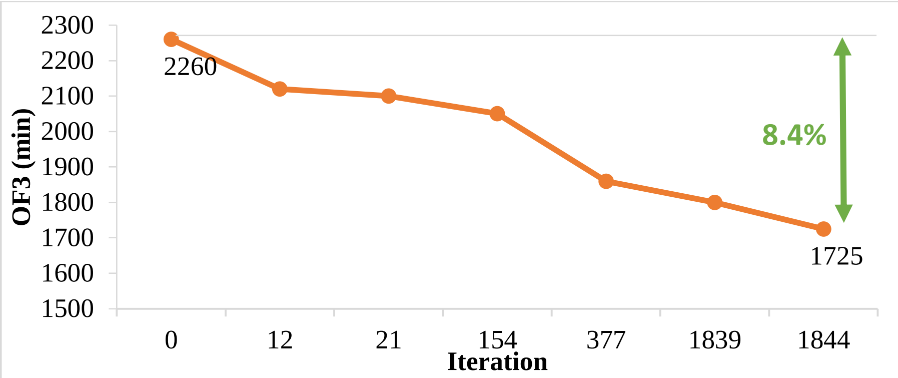

Figure 12 BiObSA MTS for makespan minimization (OF3) evolution

The production plan generated (see Figure 13) produced a total of 2640 minutes of setup time (approx. 44 hours). Comparing to the previous production plan it is noticed that the setup time increased in 460 minutes (approx. 8 hours). This further enhances the statement that the makespan minimization objective is not the best choice to increase efficiency through minimizing the setup time.

Mach.	1	2	3	4	5	6	7	8	9	Makespan	ST
M1	O13, P13									1600	0
M2	O2, P2	O14, P14								1640	300
M3	O3, P3	O6, P6	O8, P8	O9, P9						1510	610
M4	O7, P7	O10, P10	O4, P4	O5, P5						1570	320
M5	O1, P1	O12, P12								1725	300
M6	O27, P27	O21, P21	O20, P20	O19, P19						1500	300
M7	O23, P23	O24, P24	O25, P25	O22, P22						730,5	300
M8	O17, P17	O18, P18	O16, P16	O28, P28	O29, P29					1720	510
OF1	0										
OF2	14545,5										
OF3	1725										
Total ST	2640										

Figure 13 BiObSA MTS for makespan minimization (OF3) production plan

4.1.3 Computational Results Conclusions

Both production strategies showed good results in minimizing the objective functions they addressed. The MTO revealed higher complexity requiring higher temperatures and slower convergence while MTS can produced good results in less iterations and lower temperatures. The different complexity results in different performances and outcomes.

For the Mono-Objective approach MTS requires less computational capacity and zero-delay solution is obtained faster (average of 0.1 s). On the contrary the MTO algorithm requires a much larger computational capacity. The average time elapsed until zero-delay per execution is 7.0 seconds. The set of parameters that produced the best results for both Mono-Objective approaches are T_1=500, $NIST_1$=250 and R_1=0.99.

For the Bi-Objective approach the results obtained showed good results in terms of the objective function minimization. The MTO strategy reduced the total production time and makespan in 14% while the MTS strategy the reduction achieved was 19% for total production time and 8.4% for makespan. This difference between MTO and MTS is explained by the lower complexity caused by the addition of initial and final stocks.

5 Conclusions

In this paper two Simulating Annealing algorithms are proposed, MonoSA with the total delay minimization as objective function and BiObSA with the minimization of total delay and minimization of total production time or makespan minimization, for the schedule of a container plastic injection molding process.

To illustrate the algorithm performance two strategies are compared, MTO and MTS. The MTO approach presented higher complexity, requiring higher temperatures and slower convergence compared with the MTS strategy. The MTS strategy reached zero-delay in lower iterations. The results show that process complexity has high impact in the algorithm performances and the MTS presents higher performance compared with the MTO strategy.

The BiObSA MTS algorithm for the minimization of total delay and total production time was adapted to fit in the real situation at the factory. It was a challenging task since it required a deeper knowledge of all the operations and revealed the difficulty behind adapting optimization softwares to complex production stages.

Despite the low reduction in total production time (0.9%) the results obtained produced quality and reliable results for scheduling production and guarantee no production delays. The relaxed orders due dates and production slacks suggest that the factory keeps unnecessary stocks levels since the orders do not trigger enough production orders to enable exploring the full potential behind this algorithm. Nonetheless the algorithm is a strong add-on to the factory's operations.

Usually production planning at the factory is a critical task that takes a team of four employees and several hours. The results presented with this algorithm require only one person and a few seconds while the production plan developed becomes useful for the machine operators since they can easily detect production delays and assess their impact in the production sequence. Now the factory has another tool to support their daily scheduling decisions.

By analysing the work developed, the following conclusions were achieved:

- Non-exact methodologies, particularly Meta-Heuristic approaches are well suited to solve this kind of complex scheduling problems in short time.
- The production strategy that best fits the case study is the Make-To-Stock strategy.
- The algorithm that best fits the case study is the Bi-Objective for minimization of total production time.
- The parameters for each algorithm largely depend on the complexity of the case study.

Some of the work developed in this master thesis was already presented in Operation Research Congress in 2015, and published in Springer International book´s Chapter entitled *Simulated Annealing for Production Scheduling: A Case Study* Marques *et al*. [8].

The concept of productivity and efficiency is transversal to all industry sectors. Scheduling decisions are a key factor affecting these concepts and are increasingly important for companies. The work developed in this master dissertation can be easily adapted to fit into different kinds of optimization problems such as supply chain optimization or other production processes. The future work to further emphasize the importance and applicability of this kind of meta-heuristic approaches would involve the creation of a new methodology to serve as a benchmark for comparison and provide more accurate results.

6 References

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