A NEW OPTIMIZATION METHOD FOR PRODUCTION PLANNING PROBLEMS USING SIMULATED ANNEALING

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Abstract

Tactic planning or master production scheduling focuses on time and spatial decomposition of the aggregate planning targets and forecasts, as well as, forecast and provision of needed resources. This process becomes extremely hard and time consuming with the increase of number of products, resources and periods considered. In face of such obstacles, this work shows a study of an Artificial Intelligence technique called Simulated Annealing applied to the optimization of production planning problem, more specifically, Master Production Scheduling. This work reviews some of the fundamental theory of simulated annealing, the methodology for master production scheduling calculation, the applicability of simulating annealing to planning problems, most important results and suggestions for further studies.

Keywords: Master Production Scheduling; simulated annealing; optimization.

1. INTRODUCTION

This is probably one of the first works applying simulated annealing (SA) to solve Master Production Scheduling (MPS) problems optimally. MPS optimization is definitely not a new field, linear and non-linear programming, for instance, have been used to address this issue for a long time. Neither is the concept of simulated annealing applied to production problem, which has been used to solve some types of scheduling problems. However, an approach that can be "easily" implemented, that can bring good planning results to industries is the focus of this research, which sees simulated annealing as a possible technique to reach optimization at low cost.

With this in mind, this work aims at identifying if production planning optimization via simulated annealing is in fact a feasible alternative. If so, then a second objective is to understand the boundaries of its application to manufacturing planning, and estimate its advantages and disadvantages through the development a prototype system. This study presents, therefore, first results for these questions, along with experimental results based on the optimizer developed.

In this new optimization method, objectives are multiple and include minimizing inventory levels, requirements not met, capacity used and operating under safety stock levels. Input data refers mainly to production capacity, safety stock levels, batch sizes, gross requirements (forecasts and orders), initial inventory levels and planning horizon (hourly, daily, weekly and/or monthly periods are acceptable).

The present study does not compare the results obtained with simulated annealing to other heuristic. This can be found at, for instance, Vieira *et al* (2003), which compared the use of simulated annealing and genetic algorithm to the optimization of master production scheduling problems.

This paper is organized as follows: Next section presents a quick review on production planning problems and simulated annealing. Section three describes how simulated annealing can be used to solve production planning problems, particularly, MPS problems. Section four focuses on different experiments to analyze SA in MPS problems. Last section presents conclusions and suggestions for future works within this project's context.

2. PRODUCTION PLANNING AND SIMULATED ANNEALING

This section explain some of the fundamental concepts behind production planning, in particular, master production scheduling and simulated annealing.

2.1. Master production scheduling: Basics

According to the American Production and Inventory Control Society (APICS), a master production plan is a declaration of what the company expects to manufacture, which become a series of planning decisions that drives the material requirements planning (MRP) system. It represents what the company intends to produce expressed in configuration, quantities and specific dates. The master plan is not a sales forecast, which represents a demand declaration. It should take into consideration the demand, pending orders, material availability, projected ending inventory levels, capacity availability, managerial policies and goals, among others. The master plan is the result of the master production scheduling.

From the production, sales and/or operations plans, which consider products organized in families or product lines and a long time horizon, the MPS transforms general information into detailed, desegregating such plans into detailed programs, individually defined for each end product, usually written in weekly and/or monthly time periods. In other words, tactical production planning processes space and timely decomposition of the goals established by the aggregate planning (Fernandes *et al*, 2000). In case of manufacturing, tactical planning disaggregates groups of resources in machines or production lines, years in months and months in weeks, if applicable.

In general, manufacturing enterprises must have these objectives in mind: maximize customer service and resource utilization and minimize inventory levels. Ideally, this means to operate the plant on levels next to production available capacity during all the time, with inventory levels next to zero, and maximum service level. This would imply that when a customer places an order, that product would have, at that moment, to be leaving the production line towards the dispatching area. The challenge is to plan production to operate it in a comfortable steady pace, building minimum inventory, taking into consideration costs caused by changing production rates and by having inventory levels (Bonomi and Lutton, 1984).

But one knows that these are conflicting objective measures one tries to minimize inventories, for instance, not having enough products to attend unexpected orders may result in degradation of service levels. The contrary is true; having inventory is acceptable in order to meet customer demand, however too much of it will increase costs.

Production planning, MPS in special, must also take into consideration that production is generally a multi-task procedure (different operations), distributed in a multi-period discrete horizon.

To quickly show some of the complexity in creating a master plan, an example is shown below, for a single product (*product A*), and without details about available and used resources (*Resource 1 and Resource 2*) capacities. (Note that some of the MPS values on Table 1 do not equal net requirements because of insufficient capacity. Not shown)

Table 1. An example of MPS for *product A*

	Per 1	Per 2	Per 3	Per 4
On Hand	100			
Initial Inventory	100	75	125	0
Batch Size	100	100	100	100
Gross Requirements	225	250	350	200
Safety Stock	100	100	100	100
Net Requirements	300	300	400	200
MPS Resource 1	**150**	**150**	**200**	**150**
MPS Resource 2	**50**	**150**	**0**	**100**
Total MPS	**200**	**300**	**200**	**250**
Ending Inventory	75	125	0	50
Requirements met	225	250	325	200
Requirements not met	0	0	25	0
Service level	1,00	1,00	0,93	1,00
Below safety stock	25	0	100	50

On-hand inventory, safety inventory levels, batch sizes and gross requirements are given (known). Net requirements are calculated from gross requirements, safety stock and batch sizes and indicates what would be produced if there was sufficient capacity. Requirements (not) met row shows how much of the gross requirement was (not) met by the MPS and initial inventories, while the service level is the ratio between requirements met and gross requirements. Below safety stock is estimated in terms of ending inventory and expected safety stock levels.

Master production scheduling becomes a very complex problem as the number of products, number of periods, and number of resources (production lines assembly lines, machines, production cells) increase. In fact, Garey and Johnson (1979) proved that production planning problems are *NP-hard*. Yet, setup times and overtime can make this problem even more complex.

As seen previously, production planning problems usually involve conflicting objectives, like minimizing inventory and set-up times, and maximizing service levels. Because of all this, use of heuristics and meta-heuristics are suggested for the resolution of these types of problems. Several artificial intelligence meta-heuristics have been applied to optimization, among them, genetic algorithms, taboo search, ant colony, beam search and simulated annealing. This work uses simulated annealing, a random search process based on the physical cooling of high temperature materials, for the MPS problems.

2.2. Production planning optimization

Contrary to production scheduling, for instance, optimization of master production scheduling problems and lot size dimensioning are topics that are not vastly present in the literature. Below, some of the works used as a reference for this study are briefly explained.

Fernandes and Carvalho (2000) have used goal-programming strategy to a multi-objective and multi-stage production planning problem. Objectives were the feasibility and cost minimization of delayed orders, inventory, production and material acquisition. The chosen example was related to a company that manufactures springs. A total of 73 different product types were considered, and a production line had up to five different stations. Time horizon used was two weeks long.

França *et al* (1997) presented a heuristic for lot-sizing in a multi-stage production environment, and three configurations of products, periods and resources were used: (10,12,1), (10,12,2) and (17,10,1). His objective function was to minimize production costs, inventories and setups. Based on França's studies, Rodrigues and Berretta (2000) developed a genetic algorithm to solve the same problem with more precision.

Clark (2002) developed a heuristic based on local search and mathematical programming to solve lot-sizing problems found at beverage companies. The objective considered was to minimize inventory levels and delays, this one having a weight a hundred times the inventory's weight. His work considered forty-one different products, a three weeks horizon, production times and setups.

Araûjo and Clark (2001) also worked in this same idea, where setup times are very relevant, as in metal casting.

Staggemeier and Clark (2001) have surveyed lot-sizing and scheduling models, citing methods that use mathematical programming, simulated annealing, evolutive algorithms, taboo search and simple heuristics for the solution of this type of problem.

2.3. Simulated annealing

The physical annealing phenomena works through slow temperature cooling of a high temperature metal, where each temperature level represents an energy level, cooling will only finishes when the material reaches the solidification point, which will correspond to the minimum energy state. If cooling occurs too rapidly, as the material reaches solidification, it will present imperfections, which compromise its resistance, also meaning that it did not reach the minimum energy state.

In simulated annealing, the energy state (level) is represented by an objective function to be minimized. Therefore, the minimum energy level represents the optimal solution and the temperature a control parameter that helps the system to reach this minimum energy.

SA works similarly to a local search method or Hill Climbing: it looks for neighboring solutions and accepts them if they are better than the current one. However, contrary to local search, which easily gets trapped in a local minimum, SA tends to escape from such minimums through the acceptance of worse solutions. The probability of accepting a worse solution depends on the temperature (the higher the temperature, the greater the probability) and on the variation of the objective function given by the solution being evaluated (the less the variation, the greater the probability). This procedure will be explained in more detail on section 3.

Metropolis and Rosenbluth (1953) have introduced an algorithm that simulates the possibility of atoms movements based on energy gains at a given temperature:

$$P(\Delta E) = e^{(-\Delta E/kBT)} \tag{1}$$

Kirchpatrick *et al* (1983) applied Metropolis´ concepts in problem optimization, being considered as the precursor of a series of studies about simulated annealing. The problems solved by this work were the traveling salesman and the printed circuit board layout. (Bonomi and Lutton (1984) also applied this algorithm to the traveling salesman problem.)

McLaughlin (1989) compared simulated annealing with other meta-heuristics successfully in a cards game, and Connolly (1990) improved the algorithm by introducing innovations to the temperature change procedure and to the initial temperature acquisition in a quadratic distribution problem.

More recently, several other researchers have used simulated annealing in manufacturing problems. Radhakrishnan and Ventura (2000), for instance, have applied simulated annealing in production scheduling problems, with earliness and tardiness penalties and sequence-dependent setup times. Moccellin *et al* (2001) have used a hybrid algorithm combining simulated annealing and taboo search to the permutation flow shops problem. Zolfaghari and Liang (2002) made a comparative study of simulated annealing, genetic algorithms and taboo search applied to products and machines grouping, with simulated annealing given the best results out of the three techniques considered.

3. SIMULATED ANNEALING TO SOLVE MPS PROBLEMS

Simulated annealing meta-heuristic tries to minimize an objective function that incorporates to the hill climbing approach concepts from physical metal annealing process. To get out of a local optimum, SA allows the acceptance of a worse solution according to a certain probability given by: $P(\Delta E) = e^{(-\Delta E/kT)}$

Where
- P(.) is the acceptance probability
- ΔE is the objective function variation
- T is the current temperature
- k is a system constant

In the real metal annealing process, temperature must decrease gradually to avoid defects (cracks) in the metal surface. In simulated annealing, such defects will correspond to reaching a poor solution. Next sub-sections detail relevant components of the simulated annealing method implemented in this project.

3.1. The objective function

Simulated annealing, as other search methods, minimizes an object function that translates what one expects to obtain. In production planning, particularly in master production scheduling, it is desirable to meet requirements (demand), to operate above minimum (safety) inventory levels and to minimize inventory levels. On the other hand, there are inventory and overtime (overcapacity) costs that must be considered. Therefore, the object function must consider all of these measures.

Since these are variables with completely different scales, it is necessary to put them in a common scale, or in other words, to normalize them. For this, there are some alternatives one can think of:

(a) Considering all of the involved costs in a common scale: inventory costs, costs for not meeting requirements, overtime costs and costs for operating below recommended safety stock levels. Or,

(b) Reducing these variables to a related feasible scale given by maximum values for each variable.

In this study, the last option has been adopted since it is much simpler not to thin of monetary values at this time. Therefore, the proposed objective function used was defined as

$$\text{Minimize } \left\{ c_1\left[\frac{\overline{EI}_x}{\overline{EI}_{\max}}\right] + c_2\left[\frac{\overline{RNM}_x}{\overline{RNM}_{\max}}\right] + c_3\left[\sum_{i=1}^{r}\sum_{j=1}^{p}\max\left(\frac{CU_{ij}}{AC_{ij}} - 1;0\right)\right] + c_4\left[\frac{\overline{BSS}_x}{\overline{BSS}_{\max}}\right]\right\}$$

Where:
- x : current solution
- r : number of resources
- p : number of periods
- k : number of products
- th : total horizon

$\overline{EI}_x$: Average ending inventory level for a solution x:

$$\overline{EI}_x = \sum_{i=1}^{k} \overline{EI}_i \quad (2)$$

$\overline{EI}_{\max}$: Biggest $\overline{EI}$ found during "warm up" from the initial population created.

$\overline{RNM}_x$: Average of requirement not met for a solution x:

$$\overline{RNM}_x = \frac{\sum_{i=1}^{k}\sum_{j=1}^{p} RNM_{ij}}{th} \quad (3)$$

$\overline{RNM}_{\max}$: Biggest $\overline{RNM}$ found during "warm up" from the initial population created.

CU_{ij}: capacity used at resource *i* during period *j*.
AC_{ij}: available capacity at resource *i* during period *j*.
$\overline{BSS}_x$: Average below safety stock level for a solution x:

$$\overline{BSS}_x = \frac{\sum_{i=1}^{k}\sum_{j=1}^{p}\max(SS_{ij} - EI_{ij}, 0)}{th} \qquad (4)$$

$\overline{BSS}_{\max}$: Biggest $\overline{BSS}$ found during "warm up" from the initial population created.
SS_{ij}: Safety stock for product *i* at period *j*.

The C_1, C_2, C_3 and C_4 coefficients are used to set the importance of each factor to the MPS quality. Therefore, the appropriate definition for these coefficients is fundamental. The correct equation balancing depends the quality for the responses to be found.

With this objective function, there are only four adjustable parameters (C_1, C_2, C_3 and C_4), which facilitate its use and, at the same time, allow one to use different policies, by varying the parameters combination.

3.2. Input information

For the master scheduling optimization, the proposed system takes into consideration as much parameters as possible found in real industrial environments:

- Number and description of products;
- Number and description of productive resources (production lines, workstations, machines, production cells);
- Number and description of time periods and duration for each period (periods with different durations are allowed);
- Initial (on-hand) inventories – product quantities in the beginning of the planning horizon;
- Gross requirements – needed quantity per product per period, estimated from forecasting and customers orders;
- Batch sizes – production standard lot sizes per product per period;
- Safety inventory level per product per period;
- Production rate – the quantity a resource can manufacture of a product per time unit;
- Setup time per product, non-depended on operation sequence;
- Available capacity per resource per period.

3.3. Initial solution creation

With a good initial solution, the simulated annealing algorithm reaches better results in less computer time, since there are fewer chances for wasting time by searching solutions that are too far from the optimal. The proposed system one of three approaches to create its initial solution: (a) it can read a given MPS and use it as the initial solution (EIS); (b) it can create the initial solution from on a particular heuristic using the SPT (shortest processing time) dispatching rule (ISH), which means to prioritize quantities/products that require less processing time; or (c) it can use an initial solution with zero quantities (ISZ).

The pseudo code for ISH heuristic is as follows:

1. Estimate the average production time for each product to be manufactured, based on known production rates;
2. Sort products according to the above criterion;
3. Make *Period* = 1;
4. Choose the product with highest priority (shortest processing time) not yet met in the current period. If all products have been considered, go to step 7;
5. Verify which productive resource with available capacity has the smallest time to make the next quantity/product. If there is no resource with available capacity, go to step 7;
6. Allocate the requirement for the current product in this period for the chosen resource. If all requirement for this product can be met by this resource, assign this quantity/product to this resource and go to step 4, otherwise, go to step 5;
7. Make *Period* = *Period* + 1. If *Period* is greater than the last time period in the planning horizon, end heuristic; otherwise, go to step 4.

3.4. Factors that alter temperature

Two types of simulated annealing are known, according to how temperature is changed: Homogenous and non-homogenous (Zolfaghari and Liang, 2002). The homogenous algorithm runs *N* iterations at a certain temperature before changing it. At the non-homogenous SA, at every accepted (new) solution found, the algorithm changes its temperature.

The non-homogenous annealing, despite the fact that runs much faster than the homogenous, did not present satisfactory results to the MPS problem considered. Therefore, homogenous SA was considered in this study.

By using the homogenous annealing, one faces the problem of defining the appropriate value for the parameter *N*. For small *N*, being able to escape from local optimum is reduced; on the other hand, large *N* demands long computer time.

In this study N is proportional to the problem complexity and is calculated as

$$N = K \times R \times P \tag{5}$$

where:
K: number of products
R: number of resources
P: number of periods

After N iterations, search restarts from the best solution stored.

3.5. The initial temperature

In the literature, one can find different criteria for the selection of the initial temperature. In the proposed work, one hundred feasible solutions are randomly created, respecting each resource maximum available capacity. The initial temperature is the standard deviations calculated from these solutions.

Since in the beginning k = 1 and $\Delta E = T = s$,
$P(\Delta E) = e^{(-\Delta E/kT)}$
$P(\Delta E) = e^{(-s/s)}$
$P(\Delta E) = e^{-1} = 0.3679$

Therefore, the way the initial temperature is calculated will correspond to a 37% of chance to accept a worse solution in the initial temperature (this percentage will decrease as the temperature cools off).

This permits the search to quickly escape from local optima, going to a smaller search space as the temperature decreases.

3.6. Neighborhood

Choosing the neighborhood is an important aspect in simulated annealing. If the chosen neighbor result (solution) is too far from the original (different), there is a risk of running a random solution generator (performing, therefore, a random search). On the other hand, there is the risk of getting trapped into a local optimum.

In the proposed work, a neighbor solution is created by randomly altering a product quantity allocated to a resource at a given period by adding or subtracting one production batch size.

3.7. Temperature change

Temperature change allows for the algorithm to escape from a local optimum point and for continuously reaching a better solution.

It is extremely important that temperature cools off smoothly in order for the method to work properly. There are two commonly used ways for this: use of logarithmical formulae, specifically written for this purpose; and use of a decreasing factor close to one hundred percent.

The utilization of a decreasing factor of 98% gave, for the type of problem studied, better results than the logarithmic-based formulae. Therefore, change in temperature was implemented as:

$$T_{n+1} = 0.98 \times T_n \tag{6}$$

3.8. Reheating

As with the physical annealing process, to avoid premature solidification, one should reheat the system at appropriate times. Here, after M unsuccessful trials to accept a solution, temperature is raised, increasing the probability of accepting a worse solution, which, as said previously, allows the system to escape from a local optimal point.

3.9. Stopping criteria

The system will stop running when it reaches the best possible solution or when it reaches a local optimum difficult to escape from.

The best possible solution is regarded as the solution which objective function is zero; a criterion impossible to be met for most production planning problems because of conflicting objectives composing the objective function. (Remember that the best solution found is not necessarily the optimum solution.)

For the other stopping criterion, reaching a local optimum to difficult to escape, is defined as seven consecutive reheatings without improvement to the objective function.

3.10. Simulated annealing pseudo code

The main program can be generically described as:
1. Read input data;
2. If "create initial solution according to the SPT heuristic" (see Section 3.3), go to Step 3; If "create initial solution from a given MPS", go to Step 4; If "create initial solution with zero quantities", go to Step 5;
3. Create initial solution according to the SPT heuristic; Go to Step 6;
4. Read input file with detailed MPS; Go to Step 6;
5. Create initial solution with zero quantities;
6. Calculate initial temperature;
7. Run simulated annealing procedure;
8. Print/save final results.

Within these steps, the most important regards the simulated annealing procedure, which can be described as:

1. (Current) temperature = initial temperature;
   Best solution = initial solution;
2. Current solution = Best solution;
   Iterations = 0;
3. Randomly select a product *k*, a resource *r*, and a period *p*: (*k, r, p*) and increase - or decrease - the (*k, r, p*)'s quantity by one batch size;
4. If alteration is not feasible, go back to Step 3;
5. Calculate the objective function for the new solution, and the objective function variation (ΔE);
6. If the new objective function is better than the current solution, go to Step 7, otherwise, go to Step 11;
7. Current solution = new solution;
8. If the new objective function is better than the best solution, go to Step 9, otherwise, go to Step 10;
9. Best solution = new solution;
10. Apply again same alterations to the solution. Go to Step 4;
11. Randomly choose a number uniformly distributed between 0 and 1:
    g = uniform [0, 1];
12. If $g > e^{(-\Delta E/kT)}$, go to Step 13, otherwise, go to Step 17;
13. Iterations = Iterations +1;
14. If Iterations > (maximum number of iterations), go to Step 15; otherwise, go to Step 16;
15. Decrease temperature.
    Go to Step 2;
16. Current solution = new solution.
    Go to Step 3;
17. Verify if the system is frozen (number of consecutive non-accepted solutions is greater than a pre-defined value). If frozen, go to Step 18; otherwise, go to Step 3.
18. Verify is the number of reheatings met stopping criterion. If so, go to Step 20; otherwise, go to Step 19;
19. Increase temperature.
    Go to Step 2;
20. End of procedure.

4. ANALYZING SA IN MPS PROBLEMS

For practical analysis, two types of problems were chosen, a middle size problem (4, 4, 7) – four products, four resources and seven time periods; and a bigger problem (10, 4, 11). For these problems, a product can be produced by any resource.

4.1. The (4, 4, 7) scenario

For this problem, some variations were possible:
(a) With or without backordering;
(b) With or without setup times;
(c) Different initial solutions:
- Initial solution with zero quantities (ISZ);
- Initial solution created by internal heuristic (ISH) – See Section 3.3;
- Initial solution entered by a given MPS (EIS);

(d) Case 1: c_1= 1, c_2= 1, c_3= 1, and c_4= 1; and case 2: c_1= 1, c_2= 5, c_3= 1, and c_4= 1 (higher priority for requirements not met).

Using a PC with Pentium 1.2 GHz processor, the processing time for each solution varied from two to seven minutes, averaging five minutes. Table 2 shows the results for this scenario.

It is important to emphasize that conclusions regarding good or bad solutions cannot be made from results considering exclusively the objective function, since this is estimated from values relatives to $\overline{RNM}_{\max}$, $\overline{BSS}_{\max}$ and $\overline{EI}_{\max}$.

Three aspects have been analyzed for these experiments: Initial solution dependence, result degeneration when setup time is considered, and backordering effect.

Table 2. Results for the (4, 4, 7) scenario

	Setup Time	back-ordering	c1	c2	c3	c4	EI	RNM	overtime	BSS	func
ISH	With	With	1	1	1	1	7607,14	72,96	0,000	6,122	0,721
			1	5	1	1	6607,14	64,03	0,086	5,952	1,618
		Without	1	1	1	1	7892,86	22,19	0,000	6,122	0,759
			1	5	1	1	8678,57	22,19	0,000	5,952	1,835
	Without	With	1	1	1	1	7735,71	9,10	0,000	1,701	0,314
			1	5	1	1	11978,57	0,94	0,000	1,020	0,383
		Without	1	1	1	1	8235,71	4,76	0,000	0,850	0,313
			1	5	1	1	12035,71	0,00	0,000	0,680	0,348
ISZ	With	With	1	1	1	1	5800,00	73,94	0,000	10,289	0,750
			1	5	1	1	11671,43	61,65	0,038	8,461	1,381
		Without	1	1	1	1	8635,71	24,15	0,000	8,078	0,749
			1	5	1	1	15221,43	25,34	0,052	9,014	1,793
	Without	With	1	1	1	1	6764,29	8,84	0,000	4,337	0,384
			1	5	1	1	10164,29	3,66	0,000	1,105	0,360
		Without	1	1	1	1	9078,57	5,02	0,000	1,701	0,348
			1	5	1	1	13000,00	0,00	0,010	1,871	0,429
EIS	With	With	1	1	1	1	5160,43	81,08	0,009	7,218	0,740
			1	5	1	1	8406,43	79,15	0,114	11,905	2,213
		Without	1	1	1	1	6535,50	25,00	0,000	7,738	0,832
			1	5	1	1	12018,07	22,62	0,047	6,332	2,012
	Without	With	1	1	1	1	5476,86	21,11	0,000	3,401	0,368
			1	5	1	1	10070,29	7,79	0,005	1,701	0,484
		Without	1	1	1	1	5476,86	17,29	0,001	3,401	0,510
			1	5	1	1	20485,93	0,00	0,00	0,17	0,55

4.1.1. Initial solution dependence

From Table 2, it is easy to notice a large performance variation caused by the different initial solutions used. Searches using the EIS usually presented less ending inventories, on the expense of higher levels of requirements not met.

Results obtained from ISH took longer processing time before freezing.

To analyze the initial solution dependence, four different initial solutions were considered, under the two different sets of the C coefficients previously used:

a) EIS
b) Result of EIS
c) ISH
d) Result of ISH

Where "result of EIS", for instance, stands for using as initial solution the solution obtained by running the system with EIS (a given MPS).

One would expect significant improvements by using as initial solutions 'Result of EIS' instead of EIS (or 'Result of ISH' instead of ISH). Unfortunately, by looking at results shown at Table 3, this does not seem the case. Clearly, the system is trapped in a local optimum and is not able to overcome it. More elaborate experiments and an improvement in the system are needed in other to opine about the effect of initial solution on system performance.

Table 3. Initial solution effect

c1	c2	c3	c4	Initial Solution	EI	RNM	overtime	BSS
1	1	1	1	EIS	8.235,714	4,76	0	0,85034
1	1	1	1	Result of EIS	7.807,143	4,76	0	0,85034
1	5	1	1	EIS	12.035,714	0,00	0	0,680272
1	5	1	1	Result of EIS	12.035,714	0,00	0	0,680272
1	1	1	1	ISH	5.476,857	17,29	0,000533	3,401361
1	1	1	1	Result of ISH	5.476,857	17,29	0,000533	3,401361
1	5	1	1	ISH	20.485,929	0,00	0,00019	0,170068
1	5	1	1	Result of ISH	20.414,500	0,00	0,00019	0,170068

4.1.2. Result degeneration when setup time is considered

The difficulty of the system for finding better solutions increased when setup times are included, which increased processing time. No significant change on inventory levels was noticed, only some improvement on requirements not met and operating below safety inventory levels.

4.1.3. Backordering effect

Transferring requirements not met to future periods (backordering) did not cause an increase in inventory levels in order to meet future demand; on the contrary, average ending inventory had a slight decrease. The form of the objective function, which uses normalization by maximum values, was probably the reason for such effect. Requirements no met, for instance, were increased, however $\overline{RNM}_{\max}$ also increased, which ended up making a smaller effect in the objective function, which gave the idea that requirements not met were not worsen.

4.2. The (10, 4, 11) scenario

For this scenario, few variations were considered:

- All of them had setup times;
- With backordering;
- Case 1: c_1= 1, c_2= 1, c_3= 1, and c_4= 1; and case 2: c_1= 1, c_2= 5, c_3= 1, and c_4= 1;
- ISH vs. ISZ analysis.

Using a PC with Pentium 1.2 GHz processor, the processing time for each solution varied from twenty to thirty minutes. Table 4 shows the results for this scenario.

Since this is a problem where the system capacity is not enough to meet all the demand, the analysis were concentrated mainly in the study of execution time, which proved to be directly proportional to the minimum number of iterations at each temperature, therefore, to the number of products, resources and time periods.

Table 4. Results for the (10, 4, 11) scenario

	c1	c2	c3	c4	EI	RNM	overtime	BSS	func
ISH	1	1	1	1	0,656	2.749,52	0	54,6875	1,857748
	1	5	1	1	0,656	2.749,70	0	54,6875	5,282454
ISZ	1	1	1	1	0,656	2.766,46	0,0025	54,6875	1,759748
	1	5	1	1	0,656	2.749,12	0,013125	54,6875	4,769129

5. CONCLUTIONS AND CONTRIBUTIONS

This study showed that simulated annealing is an efficient optimization method that can be applied to production planning problems. However, despite significant improvement in performance, it does have some limitations, such as overcoming local optimum. This was confirmed through the experiment testing different initial solutions.

It is possible that finding a better way to create neighbor solutions can solve the problem of overcoming local optimum. Currently, most neighbor solutions differ only by one batch size (neighbors too close). Future studies should considered bigger differences among neighbor solutions (longer steps) in order to overcome this problem.

In the current configuration, the strategy to escape from a local minimum is to repeat the procedure a number of times in the same temperature. This seemed to be an efficient method, however, its drawback relates to the long processing time required. It is very important, therefore, to balance the available processing time and the quality of the results expected.

Simulated annealing, as other meta-heuristics, follows precisely what is indicated by the objective function. In the study presented, the objective function normalizes the performance measures considered in comparison to their maximum expected values, not considering, therefore, absolute performance values. Further studies should consider an objective function with actual costs, instead of relative values, like production, inventory and overtime costs and losses for not meeting demand.

Besides not being able to completely eliminate the premature freezing, the reheating strategy implemented has minimized its effect, which allowed the system to generate solutions close to the optimal ones, which greatly improved its performance.

The main parameter influencing the simulated annealing performance is the temperature, both the initial temperature and how it changes. If this parameter is correctly set, results will likely be good. Other artificial intelligence techniques have many parameters to be set; having only one parameter is another advantage of simulated annealing.

This work's main contributions comes from organizing and adapting several different concepts from isolated works in the areas of simulated annealing and applying them to master production scheduling. It presented new results of singular characteristics, and showed that optimization of production planning problems using simulated annealing is in fact a viable and attractive method.

6. ACKNOWLEDGMENT

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