

# PLANNING AND SCHEDULING OF PRODUCTION SYSTEM IN CONDITIONING LINE: INDUSTRIAL APPLICATION, OPTIMIZATION AND SIMULATION APPROACH

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## ABSTRACT

In this article we present an industrial application of our mathematical model that integrates planning and scheduling. Our main objective is to concretize our model and compare the real results with the theoretical ones. Our application is realized on a conditioning line of pharmaceutical products at the ECAM EPMI production laboratory. For this reason and to save time, we used Witness simulation tool. It gives an overall idea of how the line works, the Makespan of each simulation and it highlights areas for improvement. We looked for the best resulting sequence which corresponds to the minest Makespan and total production cost. Then this sequence is applied on the conditioning line of pharmaceutical products for simulation. On the other hand, we program our mathematical model with the parameters of the conditioning line under python in version 3.6 and we adopt a simulation/optimization coupling approach to verify our model.

## KEYWORDS

Production, planning, scheduling, MILP, optimization, simulation, conditioning line.

## Introduction

Over the three last decades, industries are more interested in production system. A key aspect of the industries is the integration between planning and scheduling. Planning determine the resources, technical operations, the arrangement of operations and processes needed to produce a job. The resulting product plan is executed in the operational level where operations of the jobs on machines are scheduled [1, 2]. Despite, the strong link between planning and scheduling, the integration between these two functions in manufacturing system still a real challenge for searchers [3].

Planning and scheduling are the most important key techniques of manufacturing [3, 4]. In an

integrated strategy, planning improves productivity while scheduling optimizes process series, expect that it is not always the case [5].

For entities, compliance with deadlines is a real requirement, thus the obligation to ensure that deadlines are met at the lowest possible cost. So, we must find the best compromise between constraints of planning and scheduling [6]. For [7], there are three strategies for solving the problem of planning and scheduling

- hierarchical,
- iterative,
- integrated.

In our modulization we choose to follow the integrated strategy of resolution because planning and scheduling are considered as one problem. This strat-

egy allows to integrate the different operational constraints at the tactical level. The principle of the integrated approach aims to define an optimal production plan for a fixed sequence of the jobs at the tactical level, then yield this production plan to the operational level where it is fixed, and then its best corresponding scheduling is established [6, 8]. These operations are repeated several times to determine the best compromise between production plan and scheduling. Among the main difficulties of integrating planning and scheduling, is the consideration of a resource always available and a capability that doesn't reflect the reality. What makes the capacity becomes aggregated and therefore nothing guarantees that the proposed production plan is feasible at the scheduling level. This represent the weaknesses of the base models of [9, 10]. Consequently, this causes delays and important work in progress in the case of overestimation of the capacity and the underutilization of the capacity in the inverse case. In terms of cost, the production one increase. At the planning level, it is question of determining the sizes of production batches, whereas in scheduling it is the definition of the sequencing of the production orders on the available resources. According to the integrated strategy proposed by [10, 11], a compromise must be found between the proposed production plan at the tactical level and the best sequencing of the jobs at the operational one. The scheduling problem is defined as the location in time and space of a set of tasks, given the time constraints (a start date with a duration or an end date) and constraints on the use and availability of resources required by the tasks.

### Proposed approach

Our model aims to guarantee a feasible production plan at the scheduling level and introduce more operational constraints. The main objective of our model is to propose a feasible production plan at scheduling level, while taking into consideration the maximum of the operational constraints. We usually schedule a set of activities so that resource capacities are not exceeded and a certain criterion, or objective function, is minimized. In our case, we minimize production, inventory and setup costs without considering the backlog one. One of the major sources of the incoherence between planning and scheduling is the consideration of resources always available. So, we added to the initial model of [12] a constraint on resources availability. It expresses the nature and quantity of resources used by the activities. It also avoids the resources consumed to exceed the available capacity of the workshop in each period  $l$ .

### Nomenclature

The parameters usually used to model this MILP problem are presented below:

- $X_{i,l}$  – quantity to produce from product  $i$  in period  $l$ ,
- $Y_{i,l}$  – a setup variable that is equal to 1 if the product  $i$  is made in period  $l$  ( $X_{il} > 0$ ), 0 otherwise,
- $I_{il}^+$  – positive inventory level of product  $i$  at the end of the period  $l$ ,
- $C_i^p$  – production cost per unit of product  $i$ ,
- $C_i^{inv}$  – inventory cost per unit of product  $i$ ,
- $C_i^s$  – setup cost per unit of product  $i$ ,
- $D_{il}$  – demand for product  $i$  at period  $l$ ,
- $capa_l$  – length of period  $l$  (capacity available),
- $\alpha_{ik}$  – resources  $k$  consumed by product unit  $i$  (machines),
- $\beta_{ik}$  – consumption of fixed resources  $k$  by product unit  $i$ ,
- $capa_l^k$  – available capacity of resource  $k$  at period  $l$ ,
- $L_i$  – lead time of the product  $i$ ,
- $O$  – all operations,
- $O_{i,m,t}$  – operation of the product  $i$  to be manufactured on the resource  $m$  at period  $t$ ,
- $i(o)$  – product associated with operation  $o$ ,
- $l(o)$  – period associated with operation  $o$ ,
- $P_o^u$  – operating time of the operation  $O$  per unit of the product  $i(o)$ ,
- $S_o$  – setup time of the operation  $O$  per product unit  $i(o)$ ,
- $r(o)$  – availability date of the operation  $O$ ,
- $d(o)$  – desired end date of operation  $O$ ,
- $A$  – set of operation pairs in the product range  $(O, O') \in A$  means that operation  $O$  precedes operation  $O'$  in the operating range,
- $L$  – all the last operations in the operating ranges,
- $F$  – all the first operations in the operating ranges,
- $E$  – all the pairs of operations that must be produced on the same resource,
- $S(y)$  – all operations associated with the sequence  $y$ ,
- $(o, o') \in S(y)$  – the operation  $o$  precedes the operation  $o'$  in the sequence of a resource.

The integrated model is presented as follow:

$$\text{Minimize } \sum_{i=1}^N \sum_{l=1}^T (C_i^p X_{il} + C_i^{inv} I_{il} + C_i^s Y_{il}), \quad (1)$$

$$I_{il} = I_{il-1} + X_{il} - D_{il} \quad \forall i, l, \quad (2)$$

$$r(o_c^f) + \sum_{occ} (P_o^u X_{i(o),l(o)} + S_o Y_{i(o),l(o)}) \leq \sum_{l=1}^{l(o_c^l)} capa_l \quad \forall c \in C(y), \quad (3)$$

$$\sum_{i=1}^N \alpha_{ik} X_{il} + \sum_{i=1}^N \beta_{ik} Y_{il} \leq capa_i^k \quad \forall i, l, \quad (4)$$

$$X_{il} \leq \left( \sum_{k=1}^T D_{ik} \right) Y_{il} \quad \forall i, l, \quad (5)$$

$$X_{i,l}, I_{il} \geq 0 \quad \forall i, l, \quad (6)$$

$$Y_{il} \in \{0, 1\} \quad \forall i, l, \quad (7)$$

$$t_o \geq 0 \quad \forall o. \quad (8)$$

The objective function (1) aims to optimize the cost of production, storage and setup but without admitting the backlog cost. Constraint (2), is the equilibrium equation for the single-level case. Constraint (3), indicates that the sum of the execution and start times of operations on a path must end before the end date of the last operation of the path. Constraint (4), is the new resource availability constraint which considers the available capacity of the resources and guaranties that the resources to be consumed don't exceed the real availability to avoid the blocking that results from the unavailability of resources. Constraint (5), represents a connection

between the decision variables. Constraint (6), ensures non-negativity of batch size and stock inventory. Constraint (7), ensures that the setup variable is binary. Constraint (8), checks the non-negativity of the start dates of the operations.

## Experimental study

### Conditioning line

Due to an industrial need of an entity located in Cergy-pontoise, the planning manager resorted ECAM-EPMI to resolve the problem of planning and scheduling of the jobs in a job-shop system. Actually, ECAM-EMPI is a french engineering school accredited, it has a production laboratory that provides valuable support for the development of tools and methods for the modelling, optimization, simulation and control of production systems in general and pharmaceutical conditioning systems in particular. It is a full-scale conditioning line that represents a complete and concrete pharmaceutical manufacturing and conditioning plant. This automated transfer line is equipped with four flexible workshops controlled by a programmable logic controller, all monitored by a computerized supervision and management system.

The existing system presented in Fig. 1, consists of 7 workstations that are linked together by accumulation conveyors and allows the packaging of 3 types of products (A, B, C).



Fig. 1. Description of the packaging line for pharmaceutical products.

Each workstation allows a different operation to be performed. The first station allows the loading and departure of the pallets, then the dosing and filling of effervescent tablet of FER, B12 and then vitamin C. Then there is capping, labelling, unloading and finally packaging. The stations are connected to each other by closed-loop conveyors and another one used to package the vials. Push arms facilitate the passage of pallets from one conveyor to another and also to do the tour of the stations. At the unloading station there are two cylinders with a suction cup system that take the vials filled with effervescent tablet to pack them and then transfer the empty pallet to the conveyor to transmit it to the first station. The line is supervised by a computer where the production lines are programmed, production ranges are defined, and the production orders are launched.

Our modeling is based on a job-shop system where the different products (A, B, C) go through all the workstations in a different order. Each product consists of three types of effervescent round tablets, such as FER, B12 and vitamin C.

Each product has a specific order and percentage of each vitamin as shown in Table 1.

Table 1  
Percentages of each vitamin in the three products.

	Product A	Product B	Product C
FER	20%	42%	30%
B12	50%	46%	5%
Vitamin C	30%	12%	65%

The conditioning line where we make our industrial application limits us to 3X7 job-shop types because the order of labelling, capping, unloading and packaging stations cannot change from one product to another. Therefore, in this application we work with three production ranges defined according to operating times. These are related to the dosages of each pill in the vials.

### Objective

Our main objective is to make an industrial application of our mathematical model in order to validate it and verify its performance in concrete terms and also to satisfy the industrial need presented by the company. The verification of our model is done by comparing the results obtained in real operation of our system. We then propose a simulation/optimization approach that will be the subject of a concrete study to verify the performance of our approach by alternating the two phases. We start by modeling and optimizing our own model in order

to define the optimal cost and the corresponding sequence. Then, we simulate our system using Witness computer tool to have the best sequence with the optimal Makespan corresponding to conditioning line. Finally, we test the best sequence given by Witness on the conditioning line and compare it to the resulting best sequence according to its total production cost given by Python using genetic algorithm. Witness simulation is not an optimization procedure, it just allows us to model many scenarios, save the time and make comparison.

### Simulation tool: WITNESS

Witness is a flow simulation software distributed by Lanner Group, used to simulate production process and provide information on the operation of the system. It avoids simulating production under an arbitrary time period and gives an overall idea of how the production line might operate in reality according to [13]. It is also a computer simulation of the consequences of different decisions of production for [14]. Witness Software is a friendly user in a risk environment, it improves efficiency and productivity [15]. On the other hand, it is used for modeling real-life failures, retooling and preventive maintenance. Witness is efficient in predicting and solving inefficiencies that may happen in production lines such as bottlenecks, overly-idle resources, storage areas and any potential issues with respect to labor attending to the processing of parts. It is a simulation software performant for modeling discrete and continuous elements that can be in different states like: busy, waiting, in-setup, broken down, and waiting labor and blocked. The platform of the software has a variety of machines as assembly, batch, production, multiple-station, multiple-cycle and finally single machines that can be defined with specific parameters of setup and breakdown in [13].

During the optimization process, different aspects of the model are varied, and the resulting value for the objective function will be compared to previous values to see if any improvement has taken place.

### Experimental modelling

#### Simulation: conditioning line

The production system presented above was gradually modelled using Witness predefined elements. We modelled a job-shop with 3 products (A, B, C), each one with its own scheduling and different operating times. We simulated a  $3 \times 7$  job-shop, which means we have  $3!$  sequences to simulate on 7 machines. To date, Witness horizon 21 is the

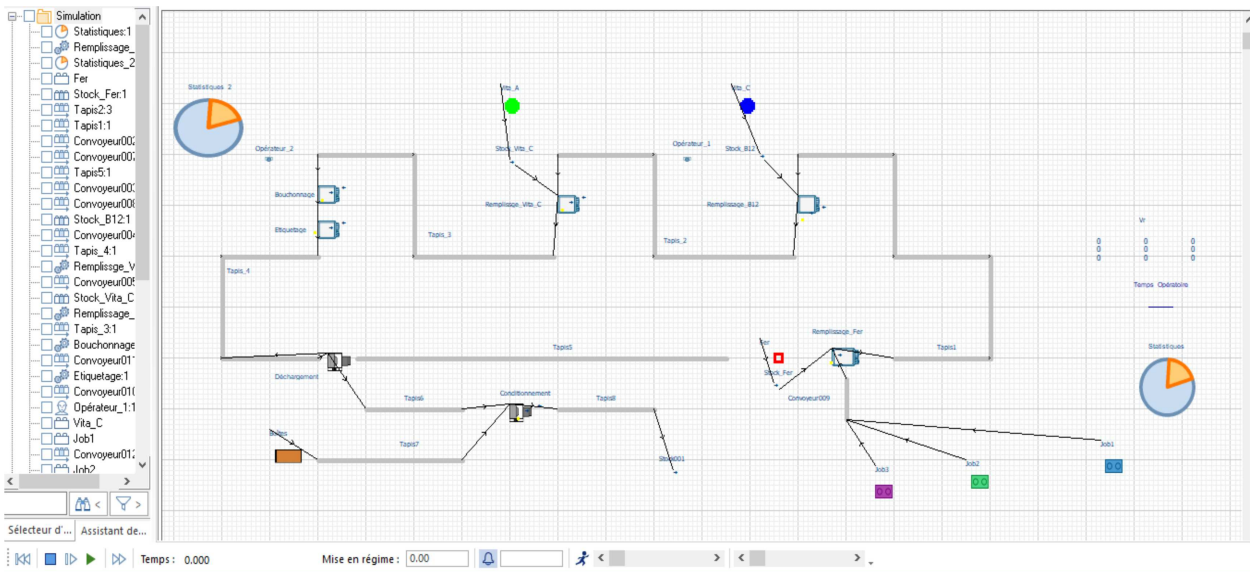


Fig. 2. Conditioning line before the launch of simulation.

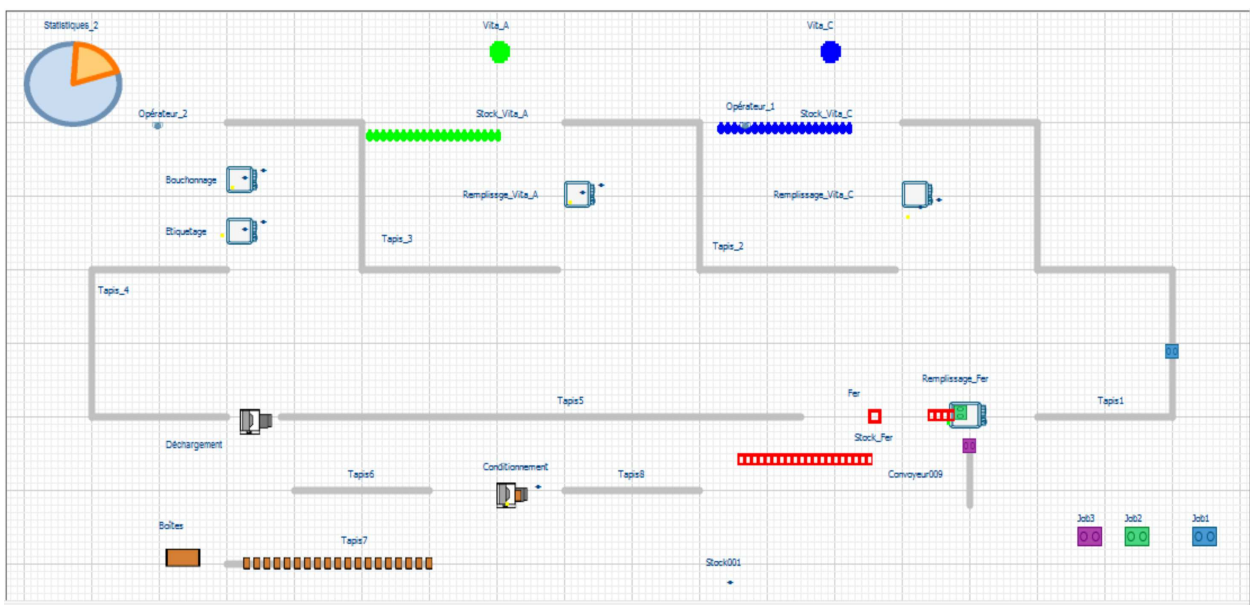


Fig. 3. Conditioning line after 48 seconds of simulation.

only tool capable of simulating a job-shop with products whose operating times are different for each product on each machine. Indeed, it represents a graphical and mathematical tool for the analytical evaluation and simulation of the system in question.

Figure 2 shows the model of the conditioning line studied before the simulation was launched. Then the following Fig. 3 shows the conditioning line after the 48-second of simulation.

### Definition of production ranges

In this application, we simulate three different production ranges defined by taking into consideration the workstations and associated operating times. Indeed, the operating times of each product on each station are related to the dosages of each vitamin filled in the workstation. The Tables 2, 3 and 4 below show the operating times of the three production ranges on the items used.

Table 2

Definition and operating times of the first range.

Post	Operating time
Filling of Fer	6.82
Filling of B12	18.96
Filling of vitamin C	7.5
Capping	21.5
Labelling	5.21
Unloading	20.5
Conditioning	28.6

Table 3

Definition and operating times of the second range.

Post	Operating time
Filling of Fer	30.03
Filling of B12	3.10
Filling of vitamin C	9.74
Capping	21.5
Labelling	5.21
Unloading	20.5
Conditioning	28.5

Table 4

Definition and operating times of the third range.

Poste	Operating time
Filling of Fer	5.72
Filling of B12	6.10
Filling of vitamin C	28.77
Capping	21.5
Labelling	5.21
Unloading	20.5
Conditioning	28.6

## Preliminary study

We started by performing  $3!$  simulations, which corresponds to 6 schedules of the 3 product ranges on the 7 workstations. Then we took for each scheduling the Makespan and the corresponding production cost in order to select the best scheduling whose performance criteria are the optimal ones. Then we compare the results obtained with those found by the real functioning and those resulting from Python. Figure 4 presents the simulation/optimization approach adopted for our problem.

In our case, the simulation block is represented by the model modeled under Witness, which allows each scheduling of the three jobs on the 7 machines to calculate the Makespan. On the other hand, the optimization block represents our own algorithm that allows us to find the optimal solution to the problem by using genetic algorithms as a method of resolution programmed in Python 3.6. This optimization gives the optimal production cost corresponding to a production plan and an optimal sequence of jobs. If the optimal sequence given from the simulation is the same as the optimization one, then our model is validated and meets the required constraints. Otherwise we must return to the optimization in order to improve the solution.

Table 5 below represents the six sequences studied with its corresponding Makespan and total production cost emerged from the programming of genetic algorithms under Python.

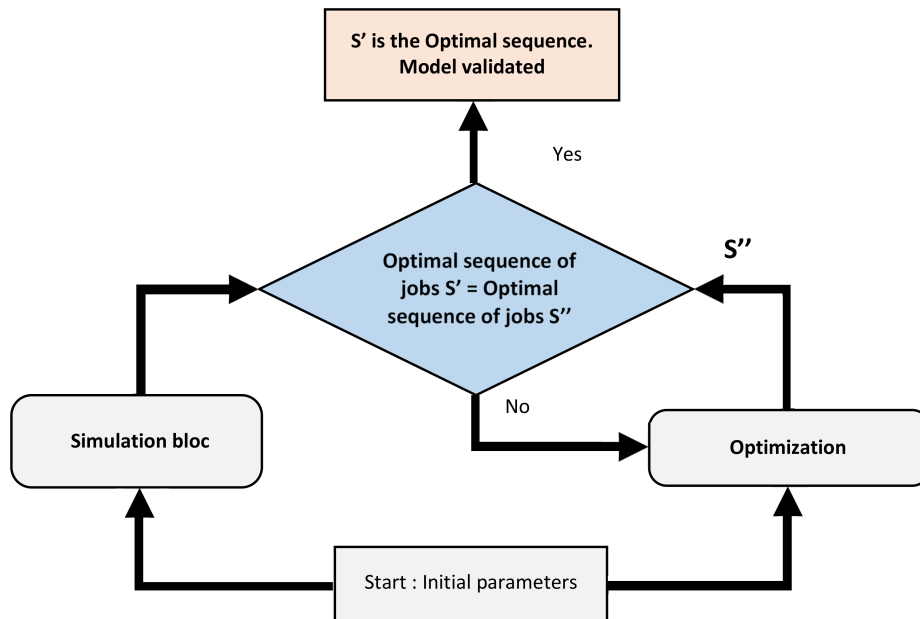


Fig. 4. Simulation/optimization approach.



Table 5  
The sequences evaluated with the Makespan and total production costs.

	Scheduling	Witness	Python
		Makespan in seconds	Production cost in monetary units
Sequence 1	A, B, C	12.35	<b>1127</b>
Sequence 2	A, C, B	12.37	<b>1243</b>
Sequence 3	B, A, C	14.40	<b>1051</b>
Sequence 4	B, C, A	13.13	<b>1068</b>
<b>Sequence 5</b>	<b>C, A, B</b>	<b>12.21</b>	<b>891</b>
Sequence 6	C, B, A	14.13	<b>1259</b>

According to Table 5 and the results found by simulation using Witness and the optimization using Python we can conclude that the optimal sequence is as follows: C, A, B. The simulation under Witness horizon 21 gives a Makespan of 12.21 seconds and corresponding to the 5th sequence, it has the shortest time of resolution.

Also, for the optimization under Python using genetic algorithm, the 5th sequence gives the minest total production cost 891 monetary units. Consequently, as result, we confirm the validation of our model due to the compatibility of the results between simulation and optimization and the performance of our proposed approach is asserted.

## Conclusion and perspectives

The need expressed by the industry attests to the great importance and the hard complexity of planning and scheduling and the intricacy of ensuring consistency between the production plan and the sequencing of jobs on resources. Hence the interest shown in our approach. This article represents an industrial application of our mathematical model. The industrial need presented by the company coincided with our need to verify our approach. Indeed, the conditioning line available at ECAM EPMI consists of a set of production stations, each of which has an operation performed. In our case we were limited to a  $3 \times 7$  job-shop where the different products (A, B, C) go through all the workstations in a different order. To verify and validate our mathematical model we adopted a simulation/optimization approach using Witness 21 for simulation and genetic algorithms programmed under Python for optimization. For so doing, we timed the operating times of each operation on the different stations for the three products and we simulate under Witness. We obtained for the  $3!$  sequences the corresponding Makespans. The optimal one suits to the best se-

quence of jobs on resources. Then we programmed genetic algorithms under Python, and we took out the best sequence of jobs corresponding to the optimal production cost. The comparison of the best sequence resulting from the simulation and optimization is satisfactory, because the best sequence is identical and it's the optimal in terms of Makespan and total production cost. In this way we ensure the validity and performance of our proposed approach and we have satisfied the request presented to ECAM-EPMI by the industrial entity.

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