A MODELING APPROACH BASED ON MULTI-AGENT SYSTEMS TO OPTIMIZE PRODUCTION CHAIN MANAGEMENT

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ABSTRACT: *One of the challenges of Industry 4.0 is to develop and optimize the flow of data, products, and materials through supply chains. To meet these challenges, we created a multi-agent simulation model to experiment and optimize a production system. Our work focuses on optimizing production chain management in the pharmaceutical industry using modeling based on multi-agent systems and computer simulation. The main objective is to develop a simulation model with FlexSim software, analyze collaboration with external entities, and focus on flow management to make informed decisions, thus optimizing system management and performance. This article presents the model developed as a decision support tool for simulation, evaluation, management, and improvement of the performance of the production system. The system analyzes logistics strategies, calculates production costs, and simulates different scenarios. Our results demonstrate the model's effectiveness in optimizing flow management and production system performance.*

KEYWORDS: *Industry 4.0, multi-agent systems, flow management, simulation, optimization, performance.*

1 INTRODUCTION

In an increasingly competitive industrial context, companies operate in a demanding environment [1]. They are faced with the need to diversify their production or specialize, and to establish relationships with a growing number of partners. This evolution leads them to form a network known as the "logistics chain". Supply chain management involves the sharing of information and the redistribution of activities between the various links in the chain [2]. For more than two decades, supply chain management has been an essential element in boosting corporate competitiveness. Originally, this concept simply represented an extension of logistics practices to encompass a growing number of partners [3, 4]. Nowadays, the supply chain is the point of convergence for practices from various backgrounds, such as quality management, product design, customer service, decision support, and so on [4]. Many companies and researchers are recognizing the benefits of effective supply chain management [5]. Studies converge on the conclusion that this management positively impacts overall company performance, particularly operational performance (customer service, response time, inventory levels, etc.). It was against this backdrop that the Supply

Chain (SC) concept emerged to meet these new requirements. The main objective lies in the efficient management of flows, involving the optimization of costs related to inventory management, storage, packaging, transport, etc. This management includes not only the physical flows of products but also the associated information flows, from the initial supplier to the end customer [6]. Efficient supply chain management therefore requires the participation and collaboration of several autonomous agents to achieve the objectives [6].

In this context, and to optimize their performance, companies must coordinate their activities to manage flows globally throughout each chain. They are constantly called upon to make agile decisions that benefit all stakeholders. A new approach developed in recent years is the multi-agent approach that adapts well to the nature of production systems generally composed of several pieces of equipment, where it is necessary to integrate several functions (driving, production management, etc.) and where decisions must be made at several levels. The agent-based approach seems an interesting technology to simultaneously model actors, their behaviors, environmental uncertainties, responsiveness, autonomy, proactivity, etc. [7]. The digital transformation of the production society, driven by the development of flexible manufacturing systems and the application of advanced information and communication technologies (ICT) in production automation, creates a new paradigm of production systems, defined by a general framework known as Industry 4.0 [8]. The concept of Industry 4.0 brings many technical and organizational changes [9]. The Industry 4.0 paradigm introduces ICT that disperses information processing and decentralizes decision-making to several autonomous and intelligent entities, such as production resources, operators, and products [10]. Simulation with process optimization, therefore, becomes a crucial tool, not only for identifying problems but also for discovering optimal solutions [11]. In the context of improving production processes, modern tools such as 3D simulation environments like FlexSim are becoming a key element of management. They provide higher-quality simulation models and enable their optimization. Real-time visualization of the phenomenon under analysis enables a better understanding of production processes [12]. This helps us achieve our goal of modeling, simulating, evaluating, and improving the company's production system management.

This research pursues two distinct objectives: first, to present concisely an updated critique of multi-agent systems; and then, to elaborate modeling of the different agents involved in the specific context of a supply chain. Our study particularly focuses on modeling the production chain of an Algerian pharmaceutical company to ensure the optimization of the production system. In this context, we present a modeling and simulation of a pharmaceutical industry's production chain using FlexSim, a decision support tool. The primary objective is to confidently select the best solution and identify the most effective improvements, paving the way for a significant reduction in total production costs. Thus, this part of the research focuses on answering the following question: «How to ensure the effective management of a supply chain, by proposing a solution that is both efficient, reliable, and high-performance? ».

2 PROBLEM STATEMENT

As part of our research focused on multi-agent modeling of the pharmaceutical production chain, we have developed a model that stands out for its ability to integrate the interactions between the various players in the supply chain, to better represent the dynamics specific to our context. Our model is based on autonomous agents that interact dynamically, taking into account factors such as raw material availability, production lines, and other logistical constraints. Each agent has its characteristics. In sum, our model offers a flexible and adaptive approach to supply chain modeling, taking into account interactions between agents and enabling efficient flow management throughout the process.

3 MATHEMATICAL MODEL

Our defined model is represented as an objective function that aims to maximize the total profit generated by the production of different products. It is expressed as follows:

$$\min Z = \sum_p \sum_t XPV_{pt} * CV_p - \sum_l \sum_p \sum_t XP_{plt} * CPR_{pl} - \sum_p \sum_t XPS_{pt} * CSP_p - \sum_m \sum_t XMPA_{mt} * CAMP_m - \sum_m \sum_t XMPS_{mt} * CS_m - \sum_l \sum_p \sum_t X_{plt} * CL_{pl} \quad (1)$$

Total cost of sales for all products is calculated in the first term; production and storage costs are calculated in the second and third terms, respectively; total cost of raw material purchases and storage is considered in the fourth and fifth terms. All product launch costs across all manufacturing lines are provided in the final term.

Respecting specific constraints is essential; therefore, the following limitations are included in the suggested model:

$$\sum_l XP_{plt} + XPS_{pt-1} = XPV_{pt} + XPS_{pt} \qquad \forall p, \forall t > 1 \qquad (2)$$

$$XPV_{pt} \leq D_{pt} \qquad \forall p, \forall t \qquad (3)$$

$$XMPA_{mt} + XMPS_{mt-1} = \sum_l \sum_p XMPU_{mplt} + XMPS_{mt} \quad \forall m, \forall t > 1 \quad (4)$$

$$XP_{plt} * Pr_{mp} * W_p = XMPU_{mplt} \quad \forall p, \forall t, \forall m, \forall l \quad (5)$$

$$XPS_{pt} * V_p \leq CAPSP_p \quad \forall p, \forall t \quad (6)$$

$$XMPS_{mt} * VMP_m \leq CAPSMP_m \quad \forall m, \forall t \quad (7)$$

$$XP_{plt} \leq M * X_{plt} \quad \forall p, \forall t, \forall l \quad (8)$$

$$\sum_p TC_{pl} * X_{plt} + \sum_p TT_{pl} * XP_{plt} * W_p \leq capmax_{l,t} \quad \forall l, \forall t \quad (9)$$

$$X_{plt} \in \{0, 1\} \quad \forall p, \forall t, \forall l \quad (10)$$

Sets:

- *l* indexes production line;
- *P* indexes product;
- *m* indexes raw materials;
- *t* indexes time.

Description of constraints:

(2): Guarantees that for each product p, the sum of the quantity sold and stored in period t must be equal to the sum of the quantity produced in period t and the quantity stored in period (t-1).
(3): Demonstrates that the quantity of products sold must be equal to customer demand at most.
(4): Guarantees that, for any raw material m, the total amount consumed and stored during period t must match the total amount bought during period t and the total amount stored during a period (t-1).
(5): Establishes how much raw material is used to make each product.
(6): Guarantees that each product's storage capacity is not surpassed by the quantity of products being stored.
(7): Guarantees that the amount of raw materials kept does not surpass the amount of space that each raw material can hold.
(8): Provides that fabrication of a product p be initiated on a line l once we have an adequate amount of product.
(9): Makes assured that each line's total launch and production timeframes do not exceed its capacity.
(10): Explain the types of variables that are employed in this problem.

3.1 Computer model construction: tools and implementation- Case study

We used FlexSim software to implement our system. It is a programmable modeling environment combining all the proven power of 3D simulation, designed to model logistics and production systems in all types of industries [13]. It features a full range of powerful tools, including 3D visualization to scale and virtual reality immersion, as well as dashboards to centralize all the statistical information shedding light on system behavior and performance [14, 15]. It is not only a decision-making tool but also a powerful training and communication tool [15].

Beyond this definition, FlexSim allows for the modeling and use of the concepts of **« agent »** and **« multi-agent ».** These concepts are already implemented in it and can be easily manipulated by users of all levels through the provided functions. Indeed, the aim is to draw up a plan for producing and supplying raw materials for the production of liquid oral medicines, intending to maximize the company's profit while minimizing production costs.

For a better simulation of our multi-agent system, this part of the work focuses on determining the parameters specific to the production system. The objective is to configure the key elements that influence the operation of the production chain, and certain parameters are therefore necessary in its implementation, namely:
D_j: Product demand submitted by beneficiaries (11)
C_i: Maximum production capacity of two lines (12)
CP_i: Product production cost in both lines (13)
CS_j: Storage costs (14)
t_{ij}: Cost of transporting raw materials per unit (15)

Total manufacturing, transportation, and storage expenses are represented by the equation with the formula: $E_{ij} = tij + CPi$ (16)
The two production lines (Li), three beneficiaries (Bj), and all parameters (11, 12, 13, 14, and 15) are displayed in Table 1.

Table 1. Calculating production system variables

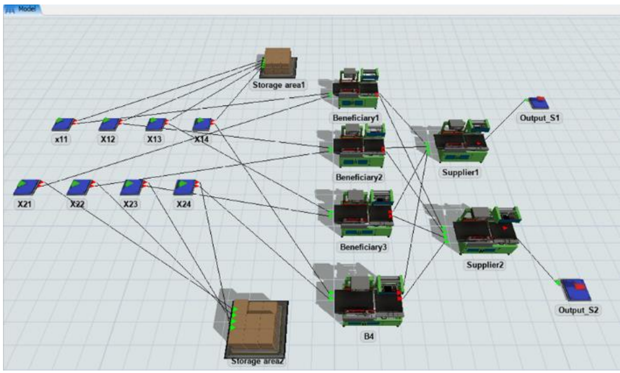
Production Line (Li)	Beneficiaries (Bj)			CSj/lot	Ci (lot)	CPi (Um1/lot)
	B1	B2	B3	B4		
L1 (Um/lot)	15292	37895	45103	10 000	208 335	1800 000
L2 (Um/lot)	22140	53451	25104	10 000	191 665	1500 000
Dj (lot)	171482	20794	38537	73867	∑Ci / ∑Dj	

Based on Table 1's data, this problem is classified as an open problem, meaning that the

[1] Monetary cost

whole production capacities ($\sum$ Ci = 400000 lots) are greater than the total demand ($\sum$ Dj = 230813 lots) that the market has issued. The ultimate objective is to minimize process costs by optimizing the decision variables Xij.

To determine the best values for the variables Xij, the objective function (1) defined by optimization criteria quantitatively states that the minimum value is to be reached. Accurate simulation models that reflect real-life conditions accurately are essential in each optimization process. Figure 1 illustrates the development of a simulation model designed specifically for this



problem.

Fig. 1 View of the model during problem simulation

Table 2 presents a description of the different resources used to build our model.

Table 2. Resources used to build our model

Object name	Type	Description
Xij	Source	8 sources representing product quantities
Storage area	Queue	2 queues representing the storage area for the additive lots
Bj	Processor	Beneficiary 1 to Beneficiary 3 represent the beneficiaries B4 in charge of production in the storehouse
Si	Processor	Supplier1, Supplier2 representing individual suppliers
Ci	Queue	Output_S1 and output_S2 are planned for each supplier, covering the production of delivered raw materials.

The model takes into account two suppliers, where the quantity of raw materials delivered is a key variable for optimizing our system. Optimization results are obtained from successive iterations involving the definition of generated flows.

It is important to note that every diverse window (Figures 1, 2, 3, 4, 5, 6, and 7) is chosen using the software's toolbox.

Model | Routing

	Setup1	Setup2	Setup3	Setup4	Setup5
Type1	Xij_output	Xij_output	finiched	finiched	finiched
Type2	Raw material_input	RM_output	finiched product_input	PF_output	additive_lot_input
Type3	Bj_input	Bj_output	Bj_output	Bj_output	Bj_output
Type4	Si_input	Si_output	Si_output	finiched	finiched
Type5	Ci_input	Ci_output	finiched	finiched	finiched

Fig. 2 Object routing content

Every source is linked to the appropriate processor, which is simulated based on the beneficiary type. Each beneficiary is then linked to a processor that represents the particular facilities of every supplier. Processor input ports are used to determine individual operation times.

The processors 1, 2, and 3 parameters are shown in Figure 3.

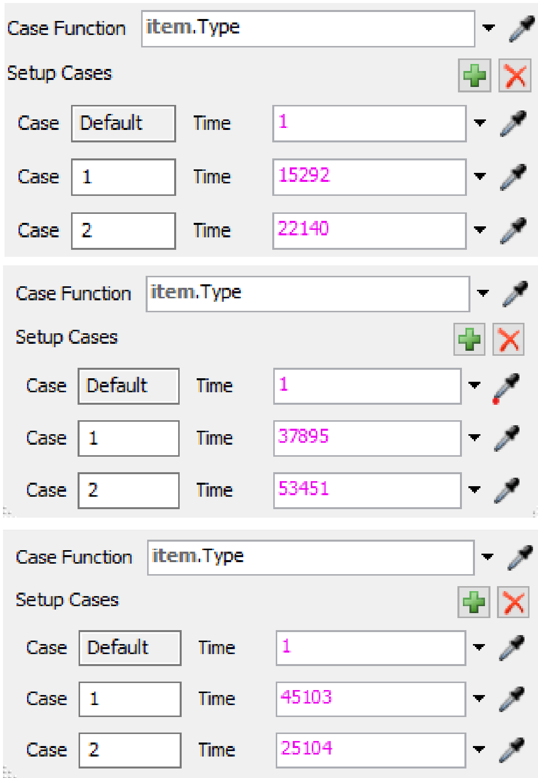


Fig. 3 Setup working time in [s] of processors 1, 2, and 3

In the case under review, the working time for each position has been kept constant following Table 1, i.e. 1 monetary unit/lot/hour. The objective function is based on the variable costs associated with storage time for additive lots, and supplier working time. Our objective function code is displayed in Figure 4.

```
/**Objective function code*/
treenode reference = param (1,2);
treenode extraData = param(1);
treenode repData = param(2);

return /**/150362*Model.parameters.x11+140086*Model.parameters.x21+
        160445*Model.parameters.x12+130150*Model.parameters.x22+
        145000*Model.parameters.x13+138250*Model.parameters.x23+
        170100*Model.parameters.x14+158451*Model.parameters.x24/**direct*/;
```

Fig. 4 An objective function defined as a performance measurement variable

To determine the optimum production plan, we need to simulate the various parameters associated with our model, as illustrated in Figure 5 below.

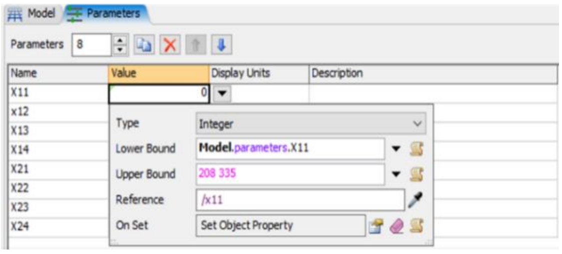


Fig 5. Parameters used to create our system

Table 3 shows the two basic scenarios for our system, while Table 4 presents the different equations for the various constraints used.

Table 3. Decision variable scenarios

	X11	X12	X13	X14	X21	X22	X23	X24
S1	1897	849	0	0	0	0	504	980
S2	0	0	1453	1315	1453	790	0	0

Table 4. Model constraint equations

	Equation
Constraint 1	$X11+X12+X13+X14 \leq 208\ 335$
Constraint 2	$X21+X22+X23+X24 \leq 191\ 665$
Constraint 3	$X11+X21 = 171482$
Constraint 4	$X12+X22 = 20794$
Constraint 5	$X13+X23 = 38537$
Constraint 6	$X14+X24 = 73867$

After examining the various aspects of our model, the aim is to minimize the objective function, reducing total production costs by adjusting the defined parameter values until optimal values are identified, to achieve the lowest level of total production costs.

3.2 Computer model simulation

The developed production system model was applied in several experimental simulations, including the simulation of the initial system state, two basic scenarios, and subsequent iterations up to the 50th. The initial simulation run, utilizing the initial data assumed during model development, generates relevant data collected and displayed on the initial simulation dashboard, as depicted in Figure 6.

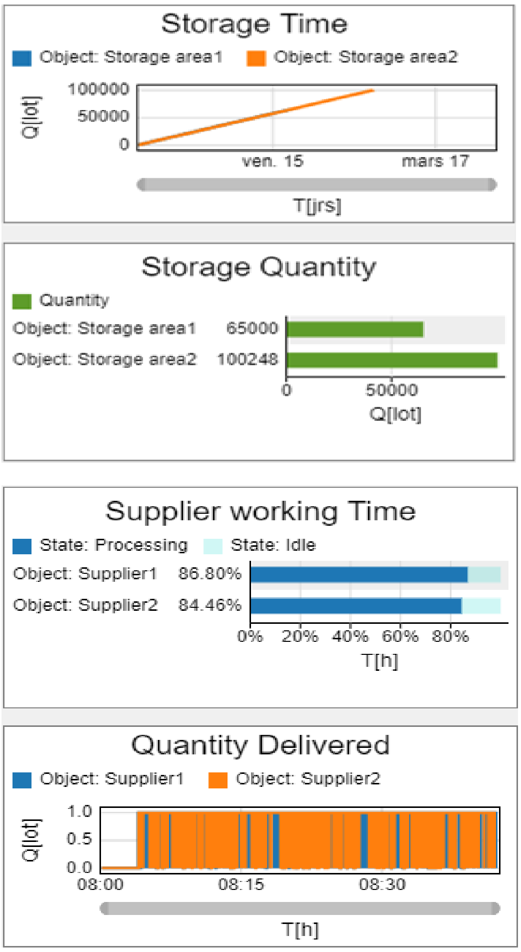


Fig 6. Screenshot of initial simulation dashboards

Analysis of the simulations reveals significant differences between the two storage zones. The first zone exhibits a shorter storage time of 190,150.704360 seconds (approximately 53 hours) and a quantity of 65,000 batches, while the second zone is characterized by a longer storage time of around 362,236.305309 seconds (approximately

100 hours) and a larger quantity of 100,248 batches as displayed by the optimizer. The work rates of the suppliers are 86.80% for Supplier 1 and 84.46% for Supplier 2.

To optimize the system, it is crucial to analyze total production costs, explore the optimization of storage time and quantity, and determine the most economical supplier to minimize transport costs. Figures 7 and 8 illustrate the simulation of the two optimization scenarios.

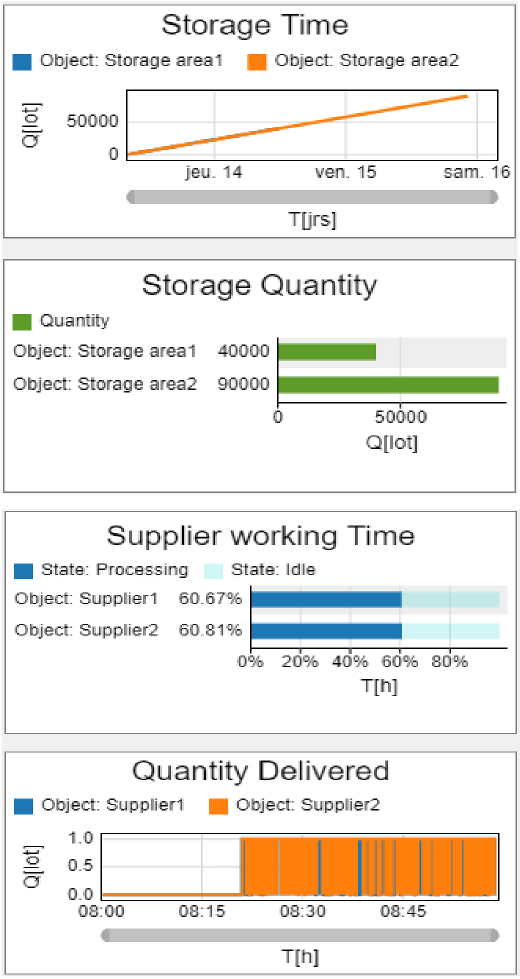


Fig 7. Screenshot of dashboards for the 1st simulation scenario.

Figure 7 depicts the first scenario, demonstrating an improvement in storage time in both zones after a certain period. The first storage zone achieves a reduced storage time of 124,118.974370 seconds (approximately 35 hours) with a stable quantity of 40,000 batches. However, the second zone, although more variable, experiences a decrease in storage time to 243,452.567655 seconds (approximately 68 hours) with a still high quantity of 90,000 batches. Notably, the displayed work rates of the suppliers have declined to 60.67% for Supplier 1 and 60.81% for Supplier 2.

The result of the second scenario simulation is depicted in Figure 8. In the first storage area, the time is recorded as 141,428.694691 seconds (approximately 39 hours), with a fixed quantity of 57,000 batches displayed by the optimizer. The storage time of the second zone, as indicated by the optimizer, is 236,952.325469 seconds (approximately 66 hours). It can be observed that supplier 1 utilized around 78.59% of their total working time, while the second supplier utilized approximately 75.34% of their working time.

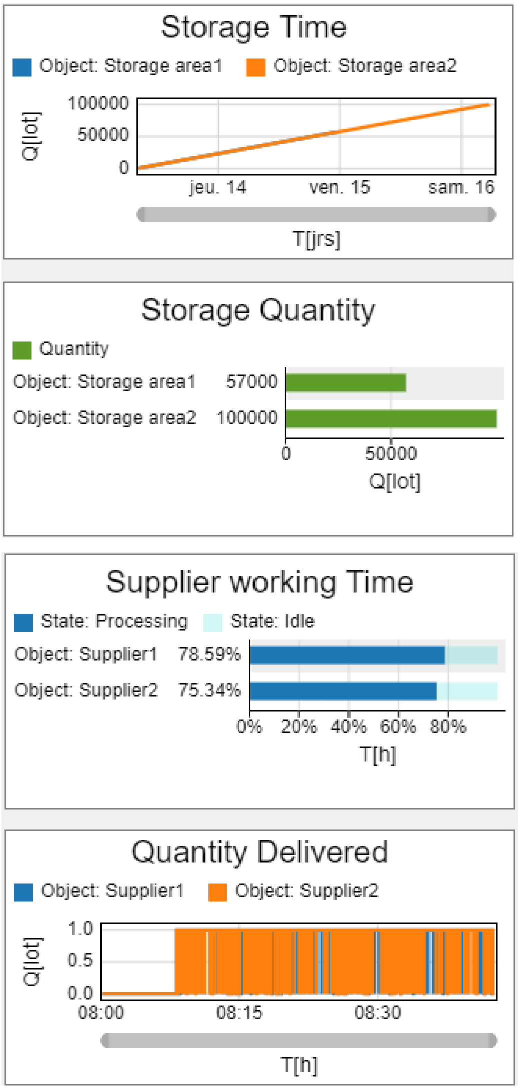


Fig 8. Screenshot of dashboards for the 2nd simulation scenario.

Our simulation after 50 iterations is depicted in Figure 9, illustrating a decrease in the storage time of the first zone to 28,518.989047 seconds (approximately 8 hours) for a quantity of 10,000 batches, and a decrease in the storage time of the second zone to 125,638.989047 seconds (approximately 35 hours) for a quantity of 14,000 batches. The work rates of suppliers 1 and 2 are similar, with rates of 38.87% and 38.56% of their total work time, respectively, despite the second supplier delivering to the company while the first did not.

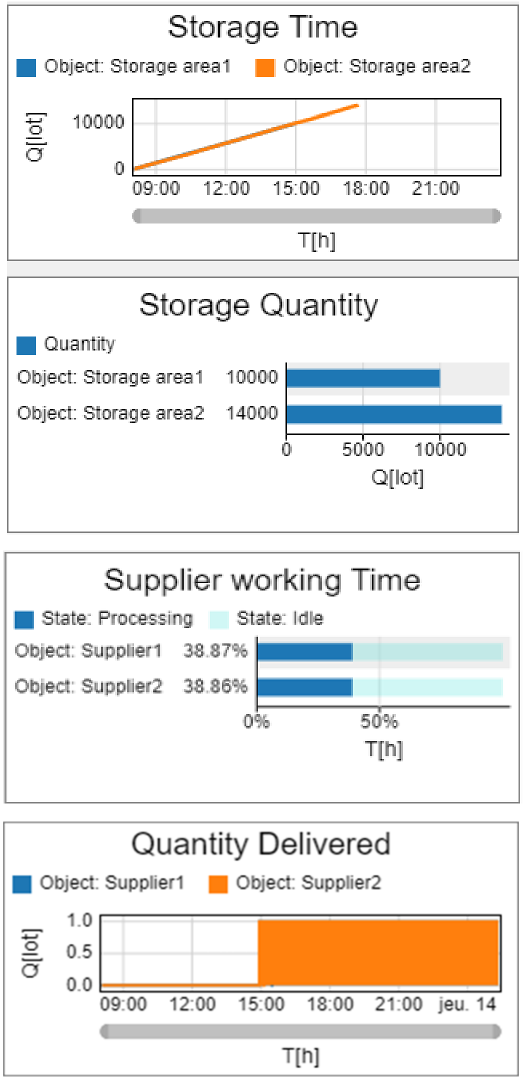


Fig 9. Screenshot of dashboards for the 50th simulation iteration

3.3 Model Optimization

Using equation 16, Table 5 summarizes the total production costs in the initial state, the first and second scenario cases, as well as the case corresponding to the optimal solution where costs are minimized (the 50th iteration).

Table 4. Summary table of our simulation results before and after optimization

	Initial state	S1	S2	Optimal solution
Total production costs (Um)	3 498 985	2 179 134	2 416 890	1 062 664

The total production cost underwent a substantial reduction, decreasing from 3,498,985 monetary units in the initial state to 1,062,664 monetary units in the optimal solution. Through the optimization of decision variables, the total production cost was significantly diminished. The optimal solution achieved at the 50th iteration represents a reduction of 69.7% in costs compared to the initial state.

4 CONCLUSION

This research demonstrates the feasibility of developing a computer simulation model of a production system. The interest of this study lies in the use of a multi-agent architecture for modeling a production system, intending to optimize supply chain flows through computer simulation using FlexSim. This architecture enables us to identify the most effective solutions for minimizing production costs and maximizing company profits.

By adopting this architecture, we can efficiently identify the most optimal solutions for minimizing production costs while maximizing company profit. Indeed, by simulating different scenarios and analyzing the results, we can determine the adjustments needed in the supply chain to optimize production flows and processes. This approach thus offers a reliable and effective method for making informed production management decisions, enabling the company to improve its competitiveness in the marketplace. In addition, the use of computer simulation reduces the risks associated with implementing changes in the production system, as it offers the possibility of testing these changes virtually before their actual application. In sum, this paper demonstrates that adopting multi-agent modeling for computer simulation of the production system is a promising approach to improving operational efficiency and profitability.

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