OPERATIONAL LEVEL-BASED CONTROL POLICIES IN SUPPLY CHAIN ENVIRONMENT

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ABSTRACT: *This paper deals with the control of the manufacturing activities of an unreliable flow-shop in a supply chain environment. In fact, the transformation system faces an unreliable upstream supply and a random replenishment delay. Our objective is to determine the manufacturing activities planning together with the raw material replenishment strategy in order to minimize the expected discounted total cost. Obviously, an analytical solution of the problem is very difficult to find. Thus a combined approach is proposed and is based on stochastic optimal control theory, discrete/continuous event simulation and genetic algorithm. Following two of our previous works (i.e., see introduction) where we proved that the integrated manufacturing and supply problem leads to a combined replenishment policy depending on the raw material and the finished products inventory levels; The contribution of this paper consists on developing an optimization module making it possible to find in a stochastic dynamic manner the best control parameters of the production and replenishment actions simultaneously with the best setup scheduling. It will be shown that it is more profitable to consider in integrated manner the manufacturing and supply control problems. In fact, for the case under study we found that the total incurred cost can be reduced up to 11 %.*

KEY WORDS : *Manufacturing activities, supply chain, replenishment, stochastic dynamic programming, simulation, genetic algorithms.*

1. INTRODUCTION

In nowadays industrial context, operations planning and control is gaining much more importance in companies' improvement process. To respond to real case problems three complex realities arises: the number of decisions, the system size / configuration and the dynamic-stochastic aspects of a given manufacturing system. One of those systems present in a vast number of industries is the flexible flow-shops. They consist on several serial stages with buffers located between them and producing multiple parts type of products. They are common in the process industry including the electronics manufacturing, the food and cosmetics, the pharmaceutical sector as well as the automotive industry.

In the aforementioned work (i.e., Hajji et al. (2007a)), we addressed the problem of production and changeover control in a class of failure prone buffered flow-shop. In the conducted literature revue, it appeared that in a dynamic stochastic context, the joint production and setup control problem has been successfully solved only for simple systems. Although, many researchers consider that even if optimal control policies can be found for realistic systems, they risk being too complicated to implement. We showed that optimal control analysis was valuable to propose joint control policies for complex systems (i.e., failure prone buffered *m* machine *n* parts type flow-shop). Thus, we were able to overcome the complexity behind the size and the dynamic stochastic aspects of a given manufacturing system (buffered flow-shops in our case).

In a supply chain context, one of the main issues arising when dealing with the manufacturing activities control consists on the relationship with the suppliers. Many works have considered the stochastic aspect of supply (i.e., supply disruptions and unavailability). Parlar et al. (1995) analyzed a periodic review inventory model with markovian supply availability. They proved the optimality of an (s, S) policy where, in a given period, s depends on the state of the supplier in the previous period. Within such a policy an economic lot of raw material is ordered when the down stream inventory level rich s. Parlar and Perry (1995) considered a stochastic inventory model where the supplier's availability process is represented as a two state continuous time markov chain. The problem was to determine the reorder point and the order quantity when system is in ON and OFF states. In the same direction, Parlar and Perry (1996) analyzed the same features with single and multiple suppliers. In their paper, Parlar and Perry stated « ideally one should use dynamic programming to discover the optimal policy that may differ from the one used in this article ». Parlar (1997) analyzed a continuous review inventory problem with random supply interruptions; they extended the continuous review (q, r) model and shoed that the form of the policy change when supplier is unavailable. Gullu et al. (1999)

and Cheng and Sethi (1999) have also considered the stochastic aspect of supply. Basically, the dynamic programming approach was employed using the concept of K-convexity to establish the optimality conditions. In these works different proofs of the optimality of (s, S) type policy were provided. Recently Lee and Wu (2006) have studied other features in the two-echelon supply chain replenishment problem. The concern was to bring answers to how we can choose a suitable replenishment policy.

In the control literature, the stochastic production and supply control problems still be considered independently. This is due, in part, to the difficulty behind the mathematical formulation of the whole system dynamic. However, the latest literature has shown that the integrated models through the intra-department planning by integrating raw material procurement and it's production is more realistic and will result to better performance than that when the planning is performed separately (Lee (2005)). In Lee's paper, an integrated joint inventory control problem based on economic lot sizes of ordering and production batch has been investigated. He showed that jointly considering the inventory supply and production costs leads to less mean total cost than that of considering the two problems separately. However, he didn't prove that the fact of considering the two problems mutually leads to the policy he considered, especially in a stochastic dynamic context.

This issue was addressed in Hajji et al. (2007b) but without considering the details of the manufacturing shop floor. In Hajji et al. (2007b) the integrated production and replenishment control problem was considered and it was shown that the optimal replenishment policy depends on the raw material and finished products inventory levels. It is interesting to note that in the literature we haven't found studies taking into account the replenishment control problem together with other manufacturing activities control.

Based on these facts, the main contribution of this paper is to propose a flexible and useful approach making it possible to address in a stochastic dynamic manner the joint replenishment, production, setup and maintenance planning problem in multi parts buffered flow-shops.

The paper is organized as follows. Section 2 states the problem and presents the main results of the optimal production and setup scheduling problem, for a *m* buffered machines multiple products manufacturing system addressed in Hajji et al. (2007a) as well as the main results of the joint production and replenishment control problem addressed in Hajji et al. (2007b). In section 3, a revue of simulation based optimization approaches is presented to introduce the proposed approach detailed in section 4. Section 5 presents the genetic algorithm and the implemented optimization module. The obtained results and related discussions are reported in section 6. The paper is concluded in section 7.

2. PROBLEM STATEMENT

The manufacturing system under study consists of an unreliable buffered flow-shop capable of producing *n* different part types P_i, $1 \le i \le n$. As shown in figure 1, the considered flow-shop consists in a serial buffered *m* machines. The machines are not completely flexible in the sense that change over time (set-up activities) between part types is not negligible. This setup conducted on the whole line involves both time (i.e., Θ_{ij}) and cost (i.e., K_{ij}). Note that, $\Theta_{ij} \ge 0 \; and \; K_{ij} \ge 0$, for, $i, j = 1, \ldots, n$, and $i \ne j$.
Part type *i* have a production rate $0 \le u_k^i(t) \le \overset{\max}{U}{}_k^i \;\; (i = 1, \ldots, n; k = 1, \ldots, m)$ on machine *k* and have an average time between orders $1/d_i$.
Machines M_k and M_{k+1}, $1 \le k \le (m-1)$ are separated by a buffer B_k. Each of which is required to store in process products P_i. The level of B_k consists on the sum of $x_k^i(t)$, $1 \le i \le n$ (i.e., inventory level of product *i* on B_k, $1 \le k \le (m-1)$).

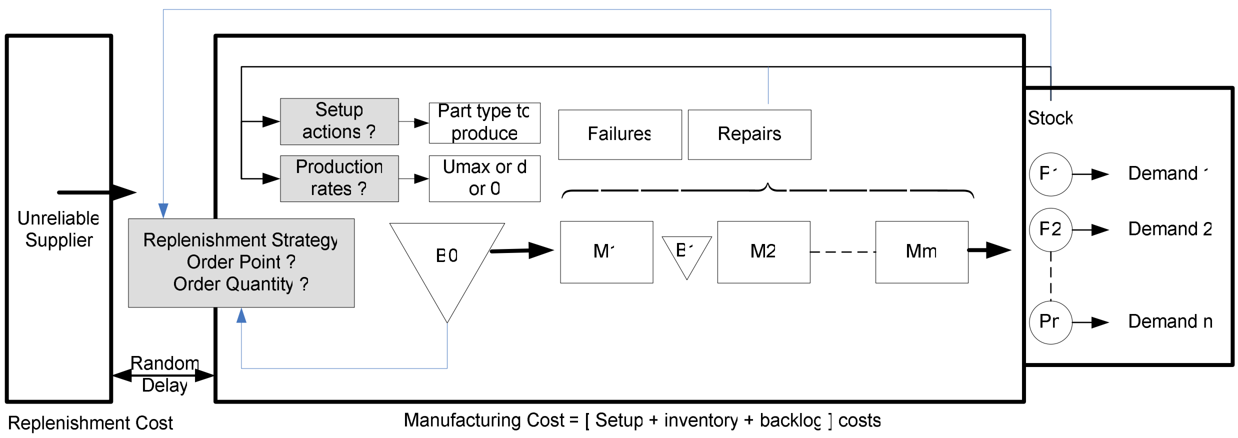

Figure 1 : *m* machines *n* parts flow-shop system in supply chain environment

The difference between actual production and downstream demand at any time represents the surplus of a part type. For buffers $B_k, 1 \le k \le (m-1)$ the difference is always positive (i.e, inventory costs c_{ik}^{+} are thus charged) or equal to zero (i.e., starvation of machine *k+1*), for buffer B_m the difference is positive (i.e, inventory costs c_{im}^{+} are thus charged) or negative (i.e., backlog costs c_{im}^{-} are thus charged). Note that if the capacity of the buffer B_k ($1 \le k \le (m-1)$) is reached, machine M_k could be blocked if the downstream demand is equal to zero.

Regarding the production and changeover control problem, our decision variables are production rates $u_k^i(t), i = 1,\ldots,n; k = 1,\ldots,m$ and a sequence of setups denoted by $\Omega = \{(\tau_0, i_0 i_1), (\tau_1, i_1 i_2), \ldots\}$. A setup (τ, ij) is defined by the time τ at witch it begins and a pair *ij* denoting that the production line was already setup to produce part *i* and is being switched to be able to produce part *j*. Section 2.1 summarizes and reviews the production and changeover mechanism developed in our previous work (i.e., Hajji et al. (2007a)).

Moreover, to prevent failures and to assure the continuity and quality of production activities, preventive maintenance actions are required. Definition and more details on the considered strategies are presented in section 2.2. When considering the manufacturing system in its external environment, one of the main issues to consider consists on a random raw material supply. As shown in figure 1, the manufacturing system under study is facing a random supply due to periods of unavailability of the supplier and/or a random transportation delay. This issue was considered in Hajji et al. (2007b), more details on the joint optimal production and replenishment strategies are presented in section 2.2.

2.1. Production and changeover mechanisms

For the system considered in Hajji et al. (2007a), the developed parameterized heuristic can be considered as a valuable contribution, since it confirms existent results and address the multi parts issue. The developed control policy, illustrated by figure 2, point toward a modified KANBAN MHCP control policies. Such a heuristic can be employed, after optimization of the correspondent parameters, to control the production and the changeovers on multi parts multi machines flow-shops.

Without loose of generality (see Hajji et al. (2007a) for the general policies), for the two machines flow-shop two parts type we can describe and to parameterize the production policies by the following equations.

$$u_1^1(\ ) = \begin{cases} U_1^{\max 1}\, IND\{S_1 = 1\} & x_1^1 \le Z_1^1 \ \&\ x_2^1 \le Z_1^2 \\ 0 & otherwise \end{cases} \qquad (1)$$

$$u_2^1(\ ) = \begin{cases} U_2^{\max 1}\, IND\{S_1 = 1\} & x_2^1 \le Z_1^2 \\ 0 & otherwise \end{cases}$$

$$u_1^2(\ ) = \begin{cases} U_1^{\max 2}\, IND\{S_2 = 1\} & x_1^2 \le Z_2^1 \ \&\ x_2^2 \le Z_2^2 \\ 0 & otherwise \end{cases} \qquad (2)$$

$$u_2^2(\ ) = \begin{cases} U_2^{\max 2}\, IND\{S_2 = 1\} & x_2^2 \le Z_2^2 \\ 0 & otherwise \end{cases}$$

Where $Z_k^i, i, k = 1,2.$ denote the different threshes involved in the modified KANBAN mechanism and $S_i, i = 1,2.$ define the system configuration described by the following equations.

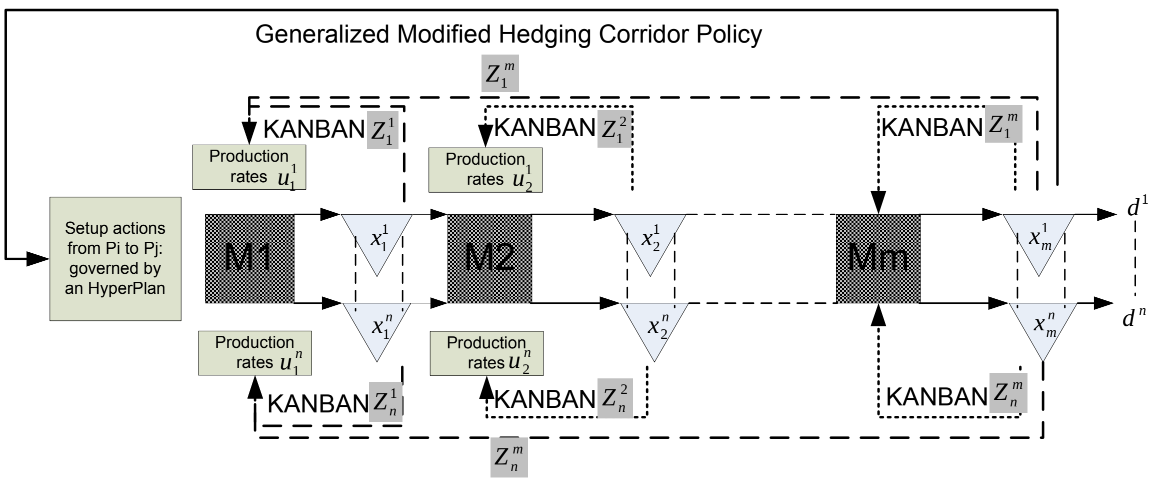

Figure 2 : *m* machines *n* parts flow-shop control mechanism

$$S_1(\ )=\begin{cases}1 & x_2^1 \le b_2 \ \& \ x_2^2 \ge a_2 \\ 0 & otherwise\end{cases} \qquad (3)$$
$$S_2(\ )=\begin{cases}1 & \left(x_2^1 \ge a_1 \ \& \ x_2^2 \le b_1\right) \| \left(x_2^2 \le c_1\right) \\ 0 & otherwise\end{cases}$$

Where $a_i, b_i, c_i, i = 1,2.$ denote the boundaries of the setup zones.

2.2. Replenishment strategy

The joint production and replenishment control problem addressed in Hajji et al. (2007b) and as shown in figure 3 consists on finding the optimal policies function of the whole system states.

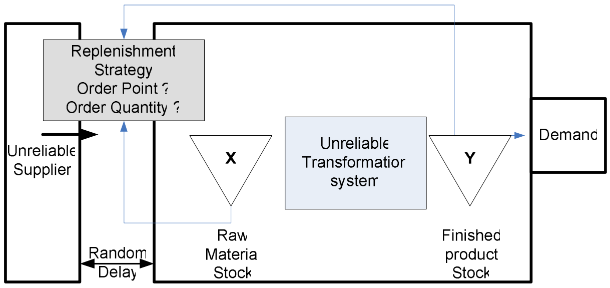

Figure 3 : Joint production and replenishment problem

The results show that the supply policy is governed by a **S**tate **D**ependant **E**conomic **O**rder **Q**uantity policy, **SD-EOQ** for short. This policy is governed by an order point and an economic order quantity, these parameters depend on the whole state of the system (***x*, *y*** and ***α***). The order point reflects the necessity to have a security raw material stock level to face a possible random delivery delay when the supplier is unavailable or a big amount of backlog accumulated after a period of unavailability of the transformation stage.

The **SD-EOQ** can be expressed by the following equations.

$$\Omega_{\text{supply}}(x,y)=\begin{cases}Q^i(x,y) & if \ x < s_R^i \ \& \ y < s_F^i \\ 0 & otherwise\end{cases} \qquad (4)$$

Recall that s_R^i and s_F^i represent the order points in respect to the raw material and finished product inventory levels x and y of part type *i* and $Q^i(x,y)$ represents the economic order quantities of part type *i* with the following constraints.

$$s_R^i \ge 0; s_F^i \ge 0 \ and \ Q^i(x,y) > 0 \qquad (5)$$

In the following section a revue of simulation based experimental approaches is presented to introduce the proposed approach.

3. SIMULATION BASED EXPERIMENTAL APPROACHES

In this section a brief review of simulation based experimental approaches to solve manufacturing system control problems is presented. Before presenting the literature revue related to the problem under study it is interesting to recall the importance of the simulation modeling in such methodology. In fact, in classical optimization approaches such as mathematical programming, it is indispensable to know in advance the transfer function. Moreover, it is much easier to involve only quantitative variables in the optimization process. This is simply not the case in a stochastic manufacturing system context where the transfer function is difficult to know in advance and which could depend on qualitative parameters. Thus, simulation modeling is a good alternative to describe the dynamic stochastic behaviour of the system. In fact, in simulation based optimization approaches, the objective function and the system constraints are described in a simulation model which consists on several networks, each of which describes a specific task in the system (i.e., demand generation, control policy, states of the machines, inventory control..., etc.). Therefore, the decision variables are the conditions under which the simulation is run, the performance measures are one or multiple responses given by the simulation.

In the literature, simulation based optimization approaches can be classified in six categories. In what follows, the two most encountered categories namely, the gradient based search methods and the heuristic methods, are discussed. For more details on the other methods see Carson and Maria (1997).

Regarding gradient based search methods; they cover finite difference estimation (Andradòttir (1998)), likelihood ratio estimation (Glynn et al. (1991)), perturbation analysis (Ho (1984)) and frequency domain experiments (Morrice and Schruben (1987)). These methods aim is to estimate the retained performance measure with respect to the decision variables.

In the other hand, heuristic methods consist on a random exploration of the admissible solutions in the whole decisions space. The search process ends when the best solution is found. At each point of the search process, the objective function value of the problem is estimated via the simulation model. Thus, no information regarding the analytic form of the objective function is required. This category covers simplex search (Azadivar and Lee (1988)), tabu search, simulated annealing (Ogbu and Smith (1990), Lee and Iwata (1991)) and genetic algorithms. All the aforementioned methods, except simulated annealing and genetic algorithms, require a system having a fixed structure during the search process and with quantitative decision variables. In our case the system under study has a variable structure. This fact imposes the recourse to simulated annealing or genetic algorithms.

It is interesting to note that previous researches and survey (Azadivar and Tompkins (1999), Chaudhry and Luo (2005) and Ruiz et al. (2007)) have demonstrated the effectiveness of Genetic algorithms solutions. In our case, our approach combines simulation and genetic algorithms to optimize the system.

4. PROPOSED APPROACH

In order to bring an approach which could be easily applied to control manufacturing systems at the operational level, the descriptive capacities of discrete/continuous event simulation models are combined with analytical models and genetic algorithms.

1-The first part of the approach consists on addressing the optimal control problem mathematically. This issue was addressed in Hajji et al. (2007a & b), the resulting parameterized production, changeover and replenishment control policies were summarized in section 2.1 and 2.2.
2-The second part consists on building an optimization module supporting the quantitative and qualitative parameters governing the production, changeover, replenishment and preventive maintenance mechanisms. This module link a parameterized simulation model with a genetic algorithm making it possible to run a genetic algorithm search process for the best solution (total incurred cost).
The search process is detailed in figure 4. It consists on running the genetic algorithm with respect to its stopping rule and evaluates each desired configuration through the simulation model.

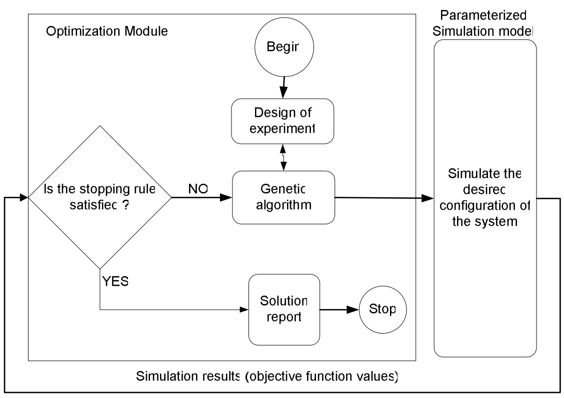

Figure 4: optimization module

3- The third part is the resulting decisional process for a given configuration of the flow-shop manufacturing system. The aforementioned configuration includes the technical and economic aspects of the system.

5. OPTIMIZATION MODULE

This section deals with the presentation of the various elements which compose the optimization module.

5.1. Genetic algorithm

The main data structures in the GA toolbox (Chipperfield et al. (1994)) are chromosomes, phenotypes, objective function values and fitness values. The chromosome structure stores an entire population in a single matrix of size $N_{ind} \times L_{ind}$, where, N_{ind} is the number of individuals and L_{ind} is the length of the chromosome structure. Phenotypes are stored in a matrix of dimension $N_{ind} \times N_{\text{var}}$ where, N_{var} is the number of decision variables. A $N_{ind} \times N_{obj}$ matrix stores the objective function values, where N_{obj} is the number of objectives. Finally, the fitness values are stored in a vector of length N_{ind} . In all of these data structures, each row corresponds to a particular individual.
The GA toolbox uses MATLAB matrix functions to build a set of versatile routines for implementing a wide range of genetic algorithm methods. In this section we outline the major procedures of the GA Toolbox and especially those used in our program.

1- Population representation and initialisation: the GA Toolbox supports binary, integer and floating-point chromosome representations. Binary and integer populations may be initialised using the Toolbox function to create populations, **crtbp**. Real-valued populations may be initialised using **crtrp**. Conversion between binary and real-values is provided by the routine **bs2rv**.

2- Fitness assignment: the fitness function transforms the raw objective function values into non-negative figures of merit for each individual. The Toolbox supports the offsetting and **scaling** method of Goldberg (1989) and the linear-**ranking** algorithm of Baker (1985).

2- Selection functions: available routines include roulette wheel selection (Goldberg (1989), routine **rws**) and stochastic universal sampling (Baker (1987), routine **sus**).

3- Crossover operators: the crossover routines recombine pairs of individuals with given probability to produce offspring. Single-point, double-point (Baker (1987)) and shuffle crossover (Caruana et al. (1989)) are implemented in the routines **xovsp**, **xovdp** and **xovsh** respectively. A general multi-point (Syswerda (1989)) crossover routine, xovmp, is also provided.

4- Mutation operators: Binary and integer mutation are performed by the routine **mut**. Real-values mutation is available using the breeder GA mutation function, **mutbga**.

The following steps summarize the employed Genetic Algorithm:
1-Population representation and initialisation: binary representation with « N_{ind} » the number of individuals and « **Preci** » the precision of the binary representation.
2- Fitness: the linear-ranking method of Baker (1985).

3-Selection: stochastic universal sampling of Baker (1987). The technique needs to fix a ratio « **GGAP** » of the best elements to keep.
4- Crossover: Single-point (Baker (1987)) with crossover probability « **Pc** ».
5-Mutation: binary mutation with probability $P_m = 1/L_{ind}$, L_{ind} is the length of the chromosome structure equal $L_{ind} = Preci \times N_{\text{var}}$.
Let « **MaxGen** » be the maximum number of generation if the stopping algorithm rule is fixed following this criteria.

5.2. Simulation model

The simulation model is build to describe the dynamic of the system governed by the production, changeover and maintenance policies defined previously and parameterized by the aforementioned parameters (section 2). These factors are considered as input of such a model and the related incurred total cost is defined as its output. The combined discrete/continuous parameterized simulation model is developed using the Visual SLAM language (Pritsker & O'Reilly (1999)) with C sub-routines. It is interesting to note that the combined discrete/continuous simulation model is more flexible and reduces the execution time (Lavoie et al. (2007)).

The Visual SLAM portion is composed of various networks describing specific tasks (failure and repair events, preventive maintenance cycles, changeover and production threshold variables crossing, data exchange with Genetic algorithm, etc...). The simulation ends when current simulation time Tc reaches the defined simulation period *T_fin*. It is interesting to note that *T_fin* is defined after several offline simulations conducted to make sure that the simulation model is stable (i.e., has reached the permanent regime). Figure 5 shows a bloc diagram representation of the simulation model.

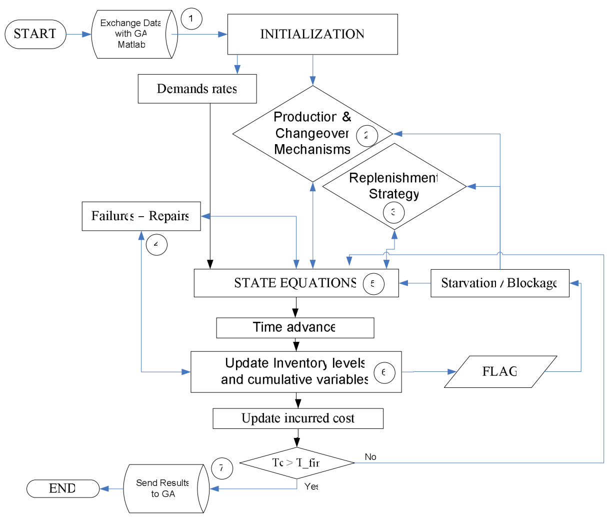

Figure 5 : simulation model bloc diagram

5.3. Genetic algorithm parameters

When dealing with genetic algorithms, the choice of the GA parameters (i.e., the precision of the binary representation and selection ratio for example) is an important issue to be taken into account since it can affect the optimization process and the final results. In the research literature the choice of these parameters is generally based on experience. One of the few studies addressing the GA parameters optimization is Pongcharoen et al. (2002) where they used design of experiment and statistical analysis approaches. In our case, this approach was used in a significant number of our research studies and it can be easily integrated to our approach.
Table 1 shows the optimum parameters obtained after running the simulations and analysing the results. We refer the reader to Gharbi et al. (2006) for more details on the different steps of the statistical analysis leading to the regression model. The optimization of this model in the experimental domain leads to the following optimal values.

	Low level	High level	Optimum
N_{ind}	60	100	100
Preci	10	30	20
GGAP	0,6	1	0.75
Pc	0,6	1	0.77
MaxGen	60	100	100

Table 1: Optimal values of the GA parameters

6. CASE STUDY

In this section, the proposed approach is applied to three buffered machines two parts manufacturing system facing an unreliable supplier and a random supply delay. For the considered control problem three decisions have to be taken namely, the production rates of each machine, the changeover actions and the replenishment strategy. These decisions are governed by the equations and the parameters given in section 2.1 and 2.2.
To summarize, our objective is to find the best production and changeover control policies parameters as well as the best replenishment strategy to minimize the expected discounted total cost of inventory, backlog, setups and ordering.
For the considered system the optimization problem include the following ***parameters:*** Z_k^i (governing the production policy for product *i* and machine *k*) ; a_i, b_i, c_i (governing the changeover actions of product *i*) and s_R^i; s_F^i; Q^i (governing the replenishment policy of product *i*.
Regarding the comparative study, the same case study but with dissociated controls is conducted. This means

that we will consider a classic replenishment strategy depending only on the raw material inventory level and governed by two parameters for each product namely the order point and the order quantity (i.e., $s_R^i; Q^i$). Our objective is to study the cost profit that one can guarantee if the two problems (manufacturing and replenishment) are considered together.
The involved unit costs are detailed in the following list:

Inventory and setup costs:

K_{ij} Setup cost to switch from P_i to P_j

c_{i3}^- Product type *i* backlog cost, incurred on finished product (buffer *3*)

c_{ik}^+ Product type *i* inventory cost incurred on buffer *k*, $1 \le k \le 3$

Replenishment cost:

K^i : Ordering cost of part type *i*.

c_R^i : Unit raw material cost of part type *i*.

c_{RH}^i : Unit raw material holding cost of part type *i*.

c_T^i : Unit of raw material transformation cost of part type *i*.

The following figure (i.e., Figure 6) illustrates the control mechanisms and the involved parameters. For the considered system we are concerned with two optimization problem. The first one under the replenishment strategy 1 (joint problem) involve 18 quantitative parameters. The second one under the replenishment strategy 2 (dissociated problem) involve 16 quantitative parameters.

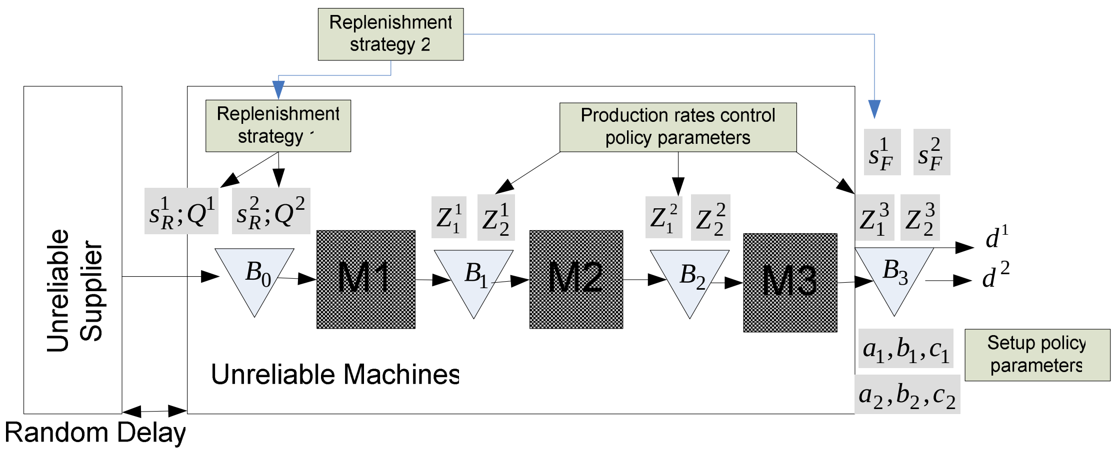

Figure 6 : *3* machines *2* parts flow-shop control policies parameters

The system parameters governing the stochastic processes, the machines configuration and the clients are given as follows:

Θ_{ij} Setup duration to switch from P_i to P_j

d^i Demand rate for part type *i*,

$U_k^{\max i}$ Maximal production rate of part type *i* on machine *k*

$MTBF_k$ Mean time between failures of machine *k* (random)

$MTTR_k$ Mean time to repair of machine *k* (random)

$MTBU$ Mean time between unavailability periods of the supplier (random)

$MTTA$ Mean time for the supplier to become available (random)

$DELAY$ Supply Delay (random)

6.1. Results under replenishment strategy 1 (RS1)

The system parameters data and the unit cost used to run the optimization module and to characterize the optimal production, setup and replenishment policies are given in table 2.
The obtained results are given in table 3. It is interesting to note, given that we are facing a homogeneous flow-shop and identical parts type with respect to the incurred costs (see table 2), that following our expectation the policies parameters are the same for the three machine and the two parts. The raison behind the choice of this case study is to insure a full control of the simulation model. For this case study, two interesting observations are concluded.
Regarding the production policy the values of the hedging levels are increasing from one stage to another. This observation confirms partially the experimental observation of Lavoie et al. (2007) (see Hajji et al (2007a) and Lavoie et al. (2007) for more details).

Regarding the changeover policy the values of c_i are infinite. This means that it does not form any more part of the policy which confirms the results of Hajji et al. (2004). In fact, this parameter is involved only in the case of different parts type.

6.2. Comparative study

In this section a comparative study involving the two aforementioned replenishment strategies (see introduction of section 6) is conducted. The first strategy (***JS***) consists on replenishment actions taking into account the whole system where the feedback information depends on the levels of raw materials and finished product. The results under this strategy were presented in section 6.1. The second strategy (***DS***) consists on replenishment actions depending only on raw materials inventory levels. The aim of this study is to confirm the robustness of the approach and at the same time the results of the numerical results of Hajji et al (2007b) where the joint production and replenishment problem have led to the first strategy. It is important to note that the results under the second strategy were obtained under the same conditions (simulation and genetic algorithm), and following the same approach under which the analysis was conducted for the first strategy (table 3).

PARAMETERS	Θ_{ij}	d^i	$U^{\max i}_k$	$MTBF_k$	$MTTR_k$
VALUES	0.3	0.35	1.2	EXP(100)	EXP(5)
PARAMETERS	$MTBU$	$MTTA$	$DELAY$	K_{ij}	c_{i3}^-
VALUES	EXP(150)	EXP(2)	EXP(6)	20	10
PARAMETERS	c_{ik}^+	K^i	c_R^i	c_{RH}^i	c_T^i
VALUES	1	20	3	1	0.1

Table 2: Data parameters

PARAMETERS	VALUES
$\begin{pmatrix} Z_1^1, Z_2^1 \\ Z_1^2, Z_2^2 \\ Z_1^3, Z_2^3 \end{pmatrix}$	$\begin{pmatrix} 8,8 \\ 10,10 \\ 16,16 \end{pmatrix}$
$\begin{pmatrix} a_1, b_1, c_1 \\ a_2, b_2, c_2 \end{pmatrix}$	$\begin{pmatrix} 7,0,-\infty \\ 7,0,-\infty \end{pmatrix}$
$\begin{pmatrix} s_R^1;\ s_F^1; Q^1 \\ s_R^2;\ s_F^2; Q^2 \end{pmatrix}$	$\begin{pmatrix} 6;\ 7;13 \\ 6;\ 7;13 \end{pmatrix}$
average total cost	42.37

Table 3: control policies parameters

Table 4 shows the optimal control policies parameters under ***JS*** and ***DS***.

It is interesting to note that the average total cost under strategy 1 (***JS***) is lower to up 11 % than that under the strategy 2 (***DS***).

Note that a sensitivity analysis was conducted under the ***JS*** and ***DS***. The results obtained have shown that the variation of the policies parameters does make sense. However, the incurred costs for all the cases are higher than those incurred under the first strategy (as shown in table 4 for the illustrated case). The improvement of the cost lies between 6 to 11 %.

To confirm these observations and hence the advantage of the proposed joint control strategies compared to that of the dissociated control strategies, a student test was performed in order to compare the performance of the two policies. The confidence interval of $c_{DS}^* - c_{JS}^*$ is given by (6).

$$\begin{aligned} &\overline{C}_{DS}^* - \overline{C}_{JS}^* - t_{\alpha/2,n-1} s.e(\overline{C}_{DS}^* - \overline{C}_{JS}^*) \\ &\le \overline{C}_{DS}^* - \overline{C}_{JS}^* \le \\ &\overline{C}_{DS}^* - \overline{C}_{JS}^* + t_{\alpha/2,n-1} s.e(\overline{C}_{DS}^* - \overline{C}_{JS}^*) \end{aligned} \quad (6)$$

where:

$t_{\alpha/2,n-1}$ is the student coefficient function of *n* and α, with *n* the number of replications (set at 10) and (1-α), the confidence level (set at 95%).

$s.e(\overline{C}_{DS}^* - \overline{C}_{JS}^*) = \frac{S_D}{\sqrt{n}}$ Standard error,

PARAMETERS	$\begin{pmatrix} Z_1^1, Z_2^1 \\ Z_1^2, Z_2^2 \\ Z_1^3, Z_2^3 \end{pmatrix}$	$\begin{pmatrix} a_1, b_1, c_1 \\ a_2, b_2, c_2 \end{pmatrix}$	$\begin{pmatrix} s_R^1; s_F^1; Q^1 \\ s_R^2; s_F^2; Q^2 \end{pmatrix}$ $\begin{pmatrix} s_R^1; Q^1 \\ s_R^2; Q^2 \end{pmatrix}$	AVAERAGE TOTAL COST
Values under strategy 1	$\begin{pmatrix} 8,8 \\ 10,10 \\ 16,16 \end{pmatrix}$	$\begin{pmatrix} 7,0,-\infty \\ 7,0,-\infty \end{pmatrix}$	$\begin{pmatrix} 6;\ 7;13 \\ 6;\ 7;13 \end{pmatrix}$	42.37
Values under strategy 2	$\begin{pmatrix} 8,8 \\ 10,10 \\ 18,18 \end{pmatrix}$	$\begin{pmatrix} 7,0,-\infty \\ 7,0,-\infty \end{pmatrix}$	$\begin{pmatrix} 8;14 \\ 8;14 \end{pmatrix}$	47.6

Table 4: control policies parameters

$$S_D^2 = \frac{1}{n-1}\left(\sum_{i=1}^{n}\left(C_{DSi}^* - C_{JSi}^*\right)^2 - n\left(\overline{C}_{DS}^* - \overline{C}_{JS}^*\right)^2\right)$$

$\overline{C}_{DS}^*$ the average optimal cost incurred under strategy 2.

$\overline{C}_{JS}^*$ the average optimal cost incurred under strategy 1.

It has been shown that in all cases, it can be concluded that C_{DS}^* - C_{JS}^* >0 at the 95% confidence level. Consequently, the first strategy gives the lower optimal cost, and furthermore, it appears that the ***JS*** is better than the ***DS***, and can be used to better approximate the optimal control policy.

7. CONCLUSION

In this paper we studied the control problem of a flow-shop manufacturing system in a supply chain environment. Our objective was to determine the manufacturing activities planning together with the raw material replenishment strategy in order to minimize the expected discounted total cost. Following two of our previous works, the contribution of this paper consists on developing an optimization module, based on stochastic optimal control theory, discrete/continuous event simulation and genetic algorithm, making it possible to find in a stochastic dynamic manner the best control parameters of the production and setup actions simultaneously with the best replenishment strategy. we have shown that it is more profitable to consider in integrated manner the manufacturing and supply control problems. In fact, we found that the total incurred cost can be reduced up to 11 % under the joint replenishment strategy ***JS***.

As it may interest the reader to know, the same approach is being applied to more complex system of 10 machines flow-shop producing 10 different parts type and facing more than one supplier. In this case, another decision should be taken and consists on the selection of the best supplier when the decision to place an order is taken.

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