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# Hierarchical Control of Production Flow based on Capacity Allocation for Real-Time Scheduling of Manufacturing Systems

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## Abstract

*This paper considers the modelling and simulation of a hierarchical production-flow control system. It uses a continuous control approach for machine capacity allocation at the design level and real time scheduling at the shop-floor level. Particularly, at the design level, the control of machine throughput has been addressed by a set of distributed and supervised fuzzy controllers. The objective is to adjust the machine’s production rates in such a way that satisfies the demand while maintaining the overall performances within acceptable limits. At the shop-floor level, the problem of scheduling of jobs is considered. In this case, the priority of jobs (actual dispatching times) is determined from the continuous production rates through a discretization procedure. A case study demonstrates the efficiency of the proposed methodology through a simulation case study.*

## 1. Introduction

Production-flow control of manufacturing systems involves decision making such as part release, routing, production orders scheduling, set-up times, etc. with the objective of producing the customer demands in needed time and with minimum costs. Particularly, in scheduling problems, the objective is to find a way to assign and sequence the use of shared resources such that production constraints are satisfied. Although traditionally addressed by: management science, operation research and industrial engineering, its complexity and importance have concentrated the efforts of different research communities, concerned with artificial intelligence [10], dynamic programming, system simulation [9][11] and control theory [4][8][19][22].

More precisely, the job-shop scheduling of a manufacturing system consisting of flexible machines and producing multiple part types has been studied by many approaches. The most developed techniques have been enumerative algorithms that provide exact solutions either by means of elaborate and sophisticated

mathematical constructs, such as linear and constraint programming [15], or by means of the branch and bound enumerative strategy, which involves search of a dynamically constructed tree that represents the solution space [3]. However, the limitations of the enumerative techniques have led to suboptimal approximation methods such as priority dispatch rules. Furthermore, artificial intelligence methods based on neural networks and fuzzy logic have been successfully applied [12][16][21]. Recently, heuristic approximation approaches based on an evolutionary algorithm has been used for optimization and performance improvements [20].

Given a deterministic job-shop structure of a manufacturing system, this paper focuses on addressing the problem of machine capacity allocation at the design and control level and the problem of real-time discrete scheduling at the shop-floor level. Indeed, at the control level, the capacity allocation problem is approached from the control theory viewpoint [4][8][19][22]. The problem is considered as a regulation of flow of parts by adjusting the machine’s processing rates. In this case, the derivation of analytical models is known to be crucial. It can be used to determine current design performance by evaluating wider quantities such as system capacity, flexibility and machine utilisation rates. However, complexity and uncertainty seriously limit the effectiveness of conventional modelling and control approaches. In the literature, methods of hierarchical control have been developed in order to overcome the system complexity analysis and its control design [8][12]. The idea is to reduce a complex problem into a set of sub-problems that are simpler to analyse.

The research reported in this paper is outgrowth of our previous work published in [19], in which the continuous production-flow control methodology of two levels has been developed with a set of distributed surplus-based controllers at the lower level and a supervisory controller at the higher level. The objective is to adjust the machine’s production rates in such a way that satisfy the demand while maintaining the overall performances within acceptable limits. In this case, since an exact analytical control design cannot be determined

in realistic manufacturing conditions, fuzzy control based on the Takagi-Sugeno system has been used to derive the local continuous-time control laws that adjust the production rates.

Moreover, production-flow control of realistic plants must satisfy multiple and possibly conflicting objectives [14]. This is the role of a supervisor that uses global performance indicators characterising the current operating mode. It provides additive components that compensate the myopic of the distributed local control when the overall system performances deviate from their overall objectives. The supervisory actions are designed such that a good compromise can be achieved between the conflicting overall objectives. These latter are quantified by fuzzy intervals since they are specified as imprecise and uncertain information.

When considering the continuous production rates provided by the control level, this paper addresses the real-time scheduling problems at the shop-floor level. For this purpose, one has to translate the obtained continuous-time production rates to a series of loading times through a sampling procedure [16]. Indeed, the controllers of all sub-machines of the same machine may conflict due to the commands that exceed the machine capacity. In this case, the decision for the actual loading part is taken using some criterion based on the computed production rate values, the surplus performances and the operation order for re-entrant flow.

The rest of the paper is organized as follows. Section 2 describes, firstly, the distributed and supervised fuzzy control methodology, originally developed in [19], and secondly, the sampling and dispatching procedure. Section 3 presents the scenario and experimental results for re-entrant and multiple-part-type real manufacturing cell taken from [16] for comparison purposes. Finally, concluding remarks are given in section 4.

## 2. Hierarchical production-flow control methodology

A production system is usually viewed as a network of a finite number of machines and buffers. Thus, when considering a production system composed of  $N$  machines ( $i = 1, \dots, N$ ) and according to the operation type (transformation, assembly and disassembly), it may be decomposed into  $N$  basic production modules  $PM(i)$ . Each one is composed of a machine  $M_i$  and its sets of upstream and downstream buffers denoted  $B_+(i)$  and  $B_-(i)$  respectively. The cardinalities of these sets distinguish the different operation types. For instance, in the case of a transformation line (Figure 1), which is considered in the sequel for the sake of simplicity, the cardinality of the sets  $B_+(i)$  and  $B_-(i)$  is respectively:  $\text{card}\{B_+(i)\} = \text{card}\{B_-(i)\} = 1$  with  $B_+(i) = \{B_{i-1}\}$  and  $B_-(i) = \{B_i\}$ . Thus, the production module can be defined as  $PM(i) = \{B_{i-1}, M_i, B_i\}$ . The assembly and disassembly procedures are

defined respectively when the cardinality of the sets  $B_+(i)$  and  $B_-(i)$  are greater than one. We can see that the sets  $PM(i)$  ( $i = 1, \dots, N$ ) can fully describe the interconnectivity of the manufacturing shop-floor system.

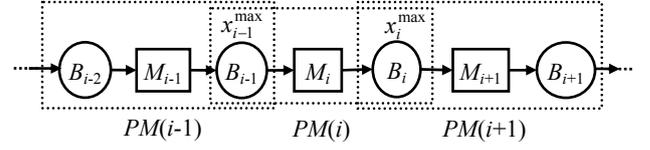


Figure 1. Transformation line.

### 2.1. Continuous production flow dynamic model

When considering the single part type transfer line depicted in Figure 1, the level of buffer  $B_i \in B_-(i)$  is given by the variable  $x_i$ , collecting the output products from machine  $M_i$  and feeding machine  $M_{i+1}$ . The increasing rate of buffer  $B_i$  is a function of the production rate  $u_i$  of the feeding machine  $M_i$ . This latter is constrained by its maximum production rate  $u_i^{\max} = 1/\tau_i$ , where the processing time  $\tau_i$  is supposed constant. Thus, the fraction of the capacity of  $M_i$  devoted for processing at time  $t$  is given by:

$$r_i(t) = u_i(t)/u_i^{\max} \quad (1)$$

It defines the control variable in this formulation, which is a function of the buffer level  $x_i$ , that is  $r_i(t) = f_i(x_i(t))$ . Further, the buffer evolution is restricted due to the machine  $M_i$  starvation. This can be accomplished by introducing the preceding buffer level  $x_{i-1}$  in the function  $f_i(\cdot)$  such that the buffer  $B_i$  will not be fed if the preceding buffer is empty. Another restriction concerns the inability of buffer  $x_i$  to increase its content while the capacity bound  $x_i^{\max}$  has been reached, since  $0 \leq x_i \leq x_i^{\max}$ .

On the other hand, the decreasing of buffer level  $x_i$  is in relation with the processing rate  $u_{i+1}$  of the downstream machine  $M_{i+1}$ . Therefore, by aggregating the increasing and decreasing rates, the dynamic model of the evolution of buffer level (production-flow)  $x_i$  is given by:

$$\dot{x}_i(t) = f_i(x_{i-1}(t), x_i(t)) \cdot u_i^{\max} - u_{i+1}(t) \quad (2)$$

with  $f_i(\cdot)$  is unknown function of their arguments to be defined.

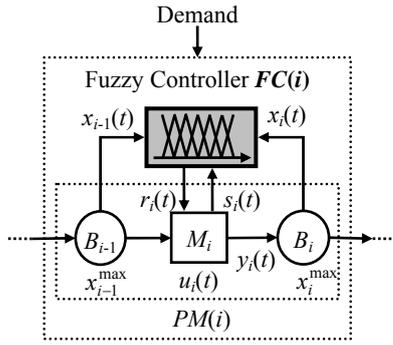
### 2.2. Fuzzy control for machine capacity allocation

Given the dynamic model of the production-flow evolution, the control objective is to adjust the production rates  $u = [u_1, \dots, u_N]$ , through an appropriate capacity allocation policy, in such a way to reach a

predefined required production (demand) while keeping all overall performance measures within their acceptable values. In this case, considering a production module  $PM(i)$ , the control law is determined through the unknown function  $f_i(\cdot)$  on the bases of the expert knowledge. Further, in order to track the demand at each production means (just-in-time production), the local surplus  $s_i$ , defining the difference between the cumulative production at this means, denoted  $y_i$ , and the demand, is taken into account in the definition of the function  $f_i(\cdot)$ . For this purpose, a fuzzy system, constituting a controller  $FC(i)$ , is used. This controller attempts to keep the upstream and downstream buffers of  $M_i$  neither full nor empty by allocating an optimised machine capacity to production. Thus, the following input variables are considered:

- the levels of upstream and downstream buffers  $x_{i-1}(t)$  and  $x_i(t)$ .
- the production surplus  $s_i(t)$  of  $PM(i)$ .

Figure 2 illustrates the fuzzy control structure of  $FC(i)$  for a transformation operation.



**Figure 2. The fuzzy control structure.**

The output variable of a controller (local control law) represents a weighting factor  $r_i(t) \in [0, 1]$  to range the production rate of  $PM(i)$  from zero to its maximum value  $u_i^{\max}$ . In the fuzzy control synthesis, this is achieved according to the two following statements:

- If the surplus is satisfying, then try to prevent starving or blocking by increasing or decreasing the production rate of the machine.
- If the surplus is either too low or too high, then produce respectively with the maximum or zero rate.

The fuzzy controller  $FC(i)$  is formalized by using a Takagi-Sugeno system [7][18][17] given by a collection of rules in the following form:

$$R_i^{(i_1, i_2, i_3)} : \text{ IF } x_{i-1} \text{ is } X_{i-1}^{i_1} \text{ and } x_i \text{ is } X_i^{i_2} \text{ and } s_i \text{ is } S_i^{i_3}, \quad (3)$$

$$\text{ Then } r_i = \varphi_i^{(i_1, i_2, i_3)}$$

where:

- The levels of the upstream and downstream buffers  $x_{i-1}$ ,  $x_i$  of  $M_i$  and the production surplus  $s_i$  represent the input variables of the premises of rules.
- $X_{i-1}^{i_1}$ ,  $X_i^{i_2}$  and  $S_i^{i_3}$  correspond respectively to the  $i_k$ th linguistic term of the input variables  $x_{i-1}$ ,  $x_i$  and  $s_i$ , taken respectively from the sets  $X_{i-1} = X_i = \{\text{Empty, Almost Empty, Normal, Almost Full, Full}\}$ ,  $S_i = \{\text{Backlog, Normal, Inventory}\}$
- $\varphi_i^{(i_1, i_2, i_3)}$  is the real value involved in the rule conclusion indexed by  $(i_1, i_2, i_3)$  that gives the fraction of capacity devoted to processing. It is taken from the values: 0, 0.25, 0.5, 0.75 or 1.

When assuming a strict partitioning of the different universes of discourse of the input variables, the output generated by the fuzzy controller is given by:

$$r_i = \sum_{(i_1, i_2, i_3) \in I} \xi_i^{(i_1, i_2, i_3)}(x_{i-1}, x_i, s_i) \cdot \varphi_i^{(i_1, i_2, i_3)} \quad (4)$$

where  $\xi_i^{(i_1, i_2, i_3)}(x_{i-1}, x_i, s_i) = \mu_{X_{i-1}^{i_1}}(x_{i-1}) \cdot \mu_{X_i^{i_2}}(x_i) \cdot \mu_{S_i^{i_3}}(s_i)$  represents the truth value of the premises of the rules, and  $I = I_1 \times I_2 \times I_3$  indicates the set of labels representing the base of rules, with  $i_v \in I_v = \{1, \dots, 5\}$  for  $v = 1, 2$  and  $i_3 \in I_3 = \{1, 2, 3\}$ . The complete base of rules for a fuzzy controller of a transformation module, built following the statements discussed above, is given in [19].

### 2.3. Supervisory based fuzzy arithmetic interval

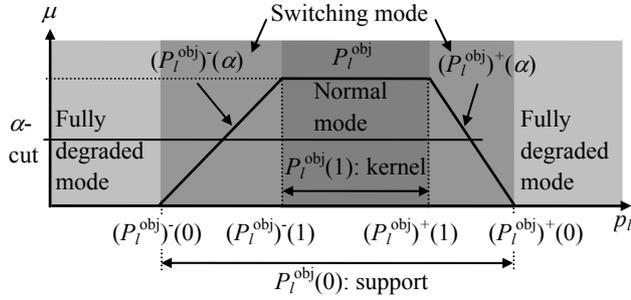
Although the distributed structure gives sometimes good control performances [4][21], it does not guarantee optimal control performances since the global information is not integrated in the distributed local control synthesis (performances are considered myopically). Indeed, the production objectives which are often conflicting are measured by global performance indicators. Therefore, a global control system combining different objectives has to be sought. In order to achieve this goal, higher supervisor based on global performance indicators is proposed [19].

Starting from a set of performance indicators  $P = \{P_1, \dots, P_L\}$  with their objectives  $P^{\text{obj}} = \{P_1^{\text{obj}}, \dots, P_L^{\text{obj}}\}$ , the supervisory controller aims at determining an additive component  $r_s = [r_{s_1}, \dots, r_{s_N}]$  to the local control law  $r_c = [r_{c_1}, \dots, r_{c_N}]$  in order to compensate the deviations of performance measures from their objectives. According to the supervisory control law, the production rate can be written as:

$$u_i(t) = (r_{c_i}(t) + r_{s_i}(t)) \cdot u_i^{\max} = r_i(t) u_i^{\max} \quad (5)$$

The key idea of the supervision function resides in: (i) the fuzzy intervals representation of the objectives and (ii) the aggregation mechanism based on the fuzzy arithmetic interval.

Indeed, a performance objective can be considered as the fuzzy quantity that should be reached. Based on expertise, this approach consists in associating a membership function  $\mu$  with the performance indicator. In this case, the grade of membership can be considered as a degree of preference. The higher degree is the more preferred value to be reached by the performance indicator. The  $\alpha$ -cut of this fuzzy objective is the set of all the values satisfying the performance at least with a preference degree of  $\alpha$  and the support is the set of values with a preference greater than 0. The kernel is the subset of the most preferred values. The complement of the support is the set of undesirable values. Thus, fuzzy intervals are an interesting tool for characterizing result reliability and developing sensitiveness studies. Moreover, fuzzy intervals encapsulate within a single formalism the optimistic case (total satisfaction) and the pessimistic one (fully unsatisfied).



**Figure 3. Trapezoidal fuzzy interval representation.**

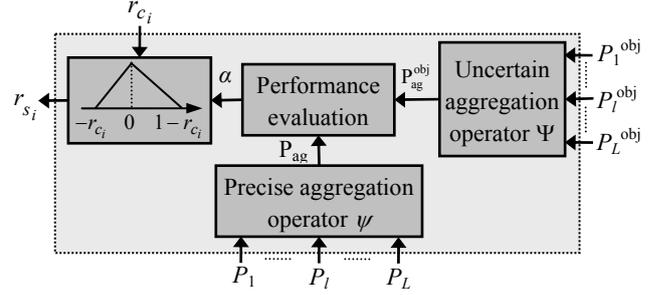
In our case, a trapezoidal fuzzy interval, denoted by  $P_i^{\text{obj}}$ , is used to represent the objective associated to the performance indicator  $P_i$  as illustrated in Figure 3. The shape of the fuzzy interval is specified by two functions that link the support and the kernel values according to the vertical dimension. These functions, denoted by  $(P_i^{\text{obj}})^-$  (the increasing part in Figure 3) and  $(P_i^{\text{obj}})^+$  (the decreasing part in Figure 3), are respectively called the left and right profiles

[2][13]. They are defined by:

$$\begin{cases} (P_i^{\text{obj}})^-(\alpha) = (1 - \alpha) \cdot (P_i^{\text{obj}})^-(0) + \alpha \cdot (P_i^{\text{obj}})^-(1) \\ (P_i^{\text{obj}})^+(\alpha) = (1 - \alpha) \cdot (P_i^{\text{obj}})^+(0) + \alpha \cdot (P_i^{\text{obj}})^+(1) \end{cases} \quad (6)$$

where  $\alpha$  is given on the vertical dimension (the  $\alpha$ -cut,  $\alpha \in [0, 1]$ )

Thus, a fuzzy interval is entirely defined by its profile functions as:  $P_i^{\text{obj}} = [(P_i^{\text{obj}})^-(\alpha), (P_i^{\text{obj}})^+(\alpha)]$ . The satisfaction may be total when the performance indicator evolves within the kernel (normal mode), not satisfactory at all if it is outside the support (fully degraded mode), and not satisfactory with different degrees when it is limited by the left or right profiles (switching mode) (Figure 3). These different situations distinguish the operating modes of the production system.



**Figure 4. The supervision principle.**

Given that the objectives are quantified by fuzzy intervals, the principle of the supervision mechanism is illustrated in Figure 4 and summarized on the following three steps:

- The aggregation of the objectives  $P^{\text{obj}} = \{P_1^{\text{obj}}, \dots, P_L^{\text{obj}}\}$  through an uncertain aggregation operator  $\Psi$ , since they are defined by fuzzy intervals [1]. This results in a fuzzy aggregated interval  $P_{\text{ag}}^{\text{obj}}$ .
- The aggregation of the performance indicator measures  $P = \{P_1, \dots, P_L\}$  using the precise version of the aggregation operator  $\Psi$ , denoted  $\psi$  [5]; the obtained result is the aggregated measure  $P_{\text{ag}}$ .
- The evaluation of the precise aggregated measure  $P_{\text{ag}}$  with regard to the fuzzy aggregated objective  $P_{\text{ag}}^{\text{obj}}$ . The result represents the satisfaction degree of the aggregated objective (the  $\alpha$ -cut) which indicates the current operating mode.

At the first step, the procedure uses arithmetic operations on fuzzy intervals. In this case, the arithmetic operations used and defined for conventional intervals can be directly extended to the fuzzy ones according to the profiles representation (6)

[2][13]. In the same way, MIN and MAX operations can be obtained from the left and right profiles [1]. For instance, when using the weighted mean operator, the resulted aggregated interval is expressed from (6), as follows:

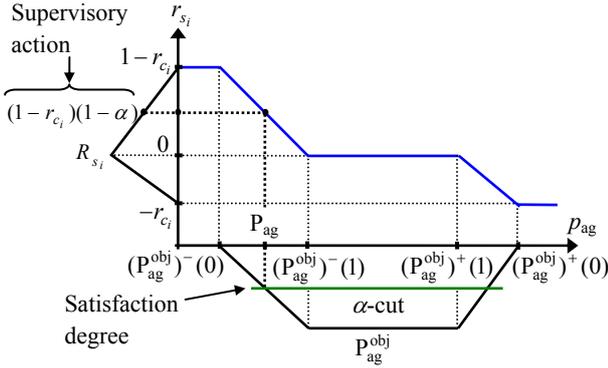
$$P_{\text{ag}}^{\text{obj}} = \Psi[P_1^{\text{obj}}(\alpha), \dots, P_L^{\text{obj}}(\alpha)] = \sum_{l=1, \dots, L}^{\oplus} w_l \cdot P_l^{\text{obj}}(\alpha) \quad (7)$$

where  $\sum^{\oplus}$  is the fuzzy addition between fuzzy intervals:  $(P_l^{\text{obj}} \oplus P_k^{\text{obj}})(\alpha) = [(P_l^{\text{obj}})^-(\alpha) + (P_k^{\text{obj}})^-(\alpha), (P_l^{\text{obj}})^+(\alpha) + (P_k^{\text{obj}})^+(\alpha)]$ .

The second step is performed in the same way by considering the precise performance indicator measures according to the precise operator [5]. Finally, the satisfaction degree of the aggregated measures is used to determine the additive component  $r_{s_i}$  (supervisory law) as illustrated in Figure 5. The different values of  $r_{s_i}$

represent a triangular fuzzy interval  $R_{s_i}$  with the support  $R_{s_i}(0) = [-r_{c_i}, 1 - r_{c_i}]$  and the kernel  $R_{s_i}(1) = 0$ .

The limit values of the supervisory law consist to allocate the maximum remaining capacity  $(1 - r_{c_i})$  or to stop the production  $(-r_{c_i})$  of the module  $PM(i)$ . The intermediate values allow to weight the support bounds of  $R_{s_i}$  according to the satisfaction degree (the  $\alpha$ -cut) of the aggregated overall objective (Figure 5). The detailed derivation of the additive component is given in [19].

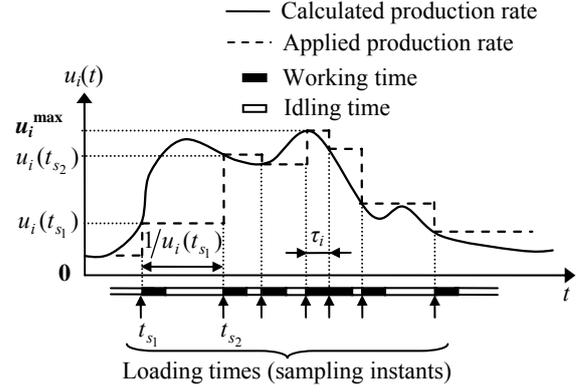


**Figure 5. The evolution of the supervisory control law.**

## 2.4. Real time scheduling

In the previous section, the production rates defined by the control laws are approximated by a continuous expression while the production operations are of discrete nature. Therefore, a dispatching policy has to be employed in order to determine the loading times of actual parts. More precisely, the obtained continuous-time control variables are translated to a dispatching time series through a sampling procedure [16]. Indeed, since the machine operation frequency is equivalent to the time between two successive machine loads, at a certain time, the sampled value is held constant during a time interval equal to its reverse. The holding period includes the operation and the idle times. Thus, the continuous time production rate is translated to a piece-wise constant function (Figure 6).

Using this definition, as the production rate evolves between 0 and  $u_i^{\max}$ , the lower bound correspond to an infinite idling time (no production) while the upper bound corresponds to the operation time (no idle time). For practical use, in order to limit the idle period when the production rate is low, the lower bound is chosen equal to 50% of its maximum.



**Figure 6. Continuous production rate discretization.**

In the case of a multiple-part type system, a machine  $M_i$  operates on different part types  $j$  such that  $j \in Q(i)$ , where  $Q(i)$  is the set of part types to be processed on  $M_i$  and its cardinality is equal to  $J$ . Each of them may involve  $K_{ij}$  ( $k = 1, \dots, K_{ij}$ ) different operations (case of re-entrant flow). In this case, the original machine  $M_i$  is virtually divided into  $N(i) = \sum_{j \in Q(i)} K_{ij}$  single-part-type sub-machines  $m_{ijk}$  [19]. Only one submachine is allowed to work at a time. Set-up times are assumed to be insignificant.

In order to deal with conflicts, actual parts are processed according to a decision function based on some criterion representing the route priority measurement. This priority is based on the control input values; the surplus and the order in which the parts visit the machine in the case of re-entrance. At the first step, priorities are made based on the highest calculated production rates. If a conflict exists, the selected submachine (the product type route) is based on surplus value with priority to the latest operation in the case of re-entrance. The following algorithm summarizes a practical implementation of the discrete dispatching procedure:

### Inputs

$$u_i \in \mathbf{R}^{N(i)}, s_i \in \mathbf{Z}^{N(i)}$$

### Outputs

The selected submachine  $m_{ijk}$  with its discrete production rate  $\hat{u}_{ijk} = u_{ijk}(t_{s_n}^*)$ , loading time  $t_{s_n}^*$  and holding time interval  $\hat{u}_{ijk}^{-1}$ .

### Begin

**1. For** all the submachines that are not idling

Select the submachine  $m_{ijk}$ , corresponding to:

$$u_{ijk}^* = \max_{j=1, \dots, J} \left\{ \max_{k=1, \dots, K_{ij}} \{u_{ijk}\} \right\}$$

**If** there is more than one submachine **then**

Select the submachine  $m_{ijk}$  corresponding to the route  $j$  with the highest negative surplus:

$$s_{ijk}^* = \max_{j=1, \dots, J} \left\{ \max_{k=1, \dots, K_{ij}} \{0, -s_{ijk}\} \right\}$$

Give the priority to the latest operation in the case of re-entrance.

Chose any submachine if there is more than one submachine satisfying these criterions.

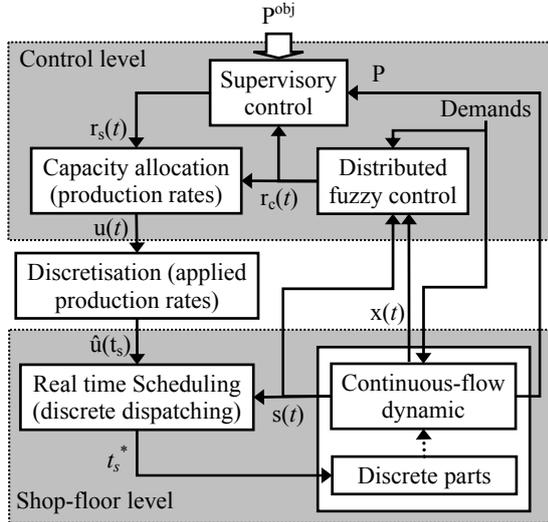
**Endif**

**Endfor**

2. The production rate  $u_{ijk}^*$  of the selected submachine is sampled at a time  $t_{s_n}^*$  ( $n = 1, 2, \dots$ ) corresponding to the loading instant. A time interval equal to the inverse of the sample is computed ( $\hat{u}_{ijk}^{-1}$  with  $\hat{u}_{ijk} = u_{ijk}(t_{s_n}^*)$ ). The values of the production rates evolving during the holding time are ignored.
3. As soon as the time interval is completed, a new sample of the production rate is considered and the process is repeated (go to step 1).

**End**

Figure 7 summarizes the production-flow scheduling methodology developed in this paper.



**Figure 7. The proposed supervised and distributed production flow scheduling.**

### 3. Simulation results

In this section, the developed methodology is illustrated through a simulation study performed on a realistic example of a manufacturing cell described in [16]. Comparisons with the results reported herein of the existing scheduling policies, specifically clear a fraction (CAF) and clear largest buffer (CLB), and the dynamic neural network scheduler (DNN) developed by the authors, are performed.

The considered system consists of five machines and produces five different part types. Due to one assembly process, six routes are defined and given in Table 1. The routes 2, 3, 4 and 5 lead to finished products. The routes 1 and 6 lead to the part types to be assembled in machine

5. The table elements show the order in which every product visits the machines. A production demand of 20 parts for each of the 5 part types has to be achieved. For simplicity, the operation times for all products on the same machine are assumed to be equal. The machine operation times are taken equal to 5, 6, 5, 4 and 3 time units respectively.

**Table 1. Part types routes.**

Route	Machine				
	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$
1		2, 4	3	1	5
2	1	2			
3		1	2		3
4	2	5	1, 4	3	
5	3	2		1	
6		2	1	3	4

The number of operations for the second machine is equal to 7 instead 6, since it serves part type 1 twice (re-entrant flow). The same holds for machine 3, where part type 4 is also served twice. Furthermore, raw materials arrive in the cell at a rate of 0.03 part per time unit, implying that for each route a raw material arrives every 34 time units, and is stored in the buffer of raw materials. All buffers in the cell are considered to have a capacity of 15 parts. Raw materials arrive to the system at the specified rate, for so long as the production of the respective product is not complete, and the buffer storing raw materials has not reached its capacity.

Based on the workload of the cell bottleneck machine, i.e. machine 2; the authors in [16] define a lower bound for the achievement of the production demand (makespan) which serves as the reference for comparison purposes. Specifically, the machine  $M_2$  (7 submachines) must process 20 parts requiring  $7 \times 20 \times 6 = 840$  time units. As the first raw material arrives in the cell at time 34, a lower bound of 874 time units is derived.

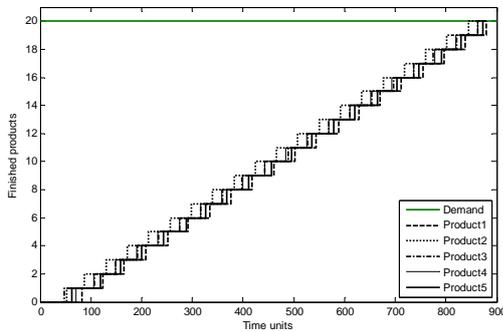
In order to evaluate the effect of the supervision, the proposed methodology is simulated in both cases: unsupervised (distributed fuzzy control – DFC) and supervised control (supervisory fuzzy control – SFC). When integrating the supervisory level, the performance indicators of the average and the instantaneous final surplus are adopted. Based on the expert knowledge, the associated objectives, expressed by fuzzy intervals, are fixed as:  $P_1^{obj} = P_2^{obj} = [-3+2\alpha, 3-2\alpha]$ . They define the tolerance domains of the finished production-surplus performances with the objective of maintaining them close to zero. When using the arithmetic mean operator (7) (with  $w_l = 0.5$ ,  $l = 1, 2$ ), the resulted aggregated interval  $P_{ag}^{obj}$  is of the same shape. The obtained results are compared to those provided in [16] and summarized in Table 2. The machine utilisation rates are given in Table 3. Moreover, Figure 8 presents the evolution of the output buffers as a function of time and the demand.

**Table 2. Simulation results.**

Methodology	Makespan	Avg. WIP	Avg. inventory	Avg. backlog	Avg. lead time
SFC	<b>880</b>	0.895	9.436	3.014	67.16
DFC	1033	1.717	8.777	5.832	188.3
DNN	963	0.506	8.17	0.00466	215.960
CAF	1044	1.347	10.848	0.00262	142.763
CLB	1083	1.149	11.468	0.00214	125.720

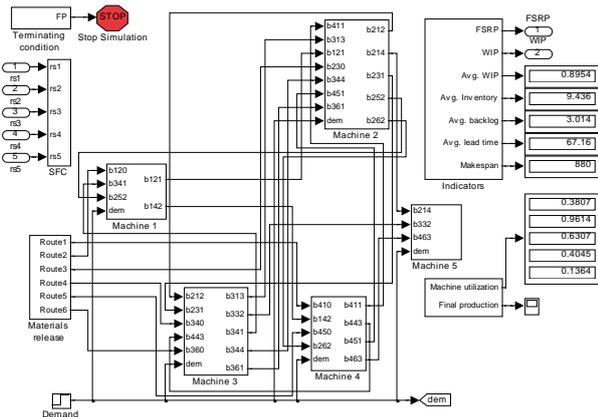
**Table 3. Machine utilisations.**

Methodology	Machine utilisation rates (%)				
	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$
SFC	38.07	<b>96.14</b>	63.07	40.45	13.64
DFC	33.88	85.96	56.15	38.33	11.62



**Figure 8. Output buffers evolution.**

Figure 9 illustrates the implementation structure of the proposed scheduling methodology by means of Matlab/Simulink and Floulib toolbox [6] (available at <http://www.listic.univ-savoie.org>).



**Figure 9. Simulation model implementation of the manufacturing cell.**

Based on the obtained results, the employment of the SFC scheduler fulfils the production demand in the shortest time interval (880 time units) compared to the results of the other tested methodologies (Table 2).

Thus, the SFC methodology achieves the production goal with a deviation of 0.68% from the optimal lower bound, representing a very efficient schedule. The utilisation rate of the bottleneck machine  $M_2$  in the case of a SFC methodology, which is approximately 96%, is improved in comparison to the rate reached with a DFC methodology (Table 3). This behaviour was expected since the supervisory goals are to maintain the final surplus within their specified domain limits by allocating the remaining production capacity when delays occur.

The four last columns of Table 2 represent average cost measures of storing parts, backlogging and lead times. The cost unit for all the performance measures is taken equal to 1 for simplicity. The SFC methodology achieves acceptable WIP, inventory and lead time costs due to the overall faster fulfilment of the demand, while the backlog cost is relatively worse than the values obtained by the conventional schedulers. These results are due to the fact that the buffers storage performances (positive surplus) and the backlog (negative surplus) are conflicting and the proposed supervisory control attempts to achieve the best compromise between them.

#### 4. Conclusion

In this paper, the problem of discrete production-flow scheduling for a manufacturing cell is considered through distributed and supervised control architecture. The hierarchical structure consists of a lower level of distributed fuzzy controllers, which is supervised by a higher level of decision-making. The lower level regulates the production flow by adjusting the machine processing rates. It uses a fuzzy controller based on the Takagi-Sugeno fuzzy system. The higher level of supervision monitors the system by using global performance indicators. The supervisory mechanism, which is based on arithmetic fuzzy interval, provides an additive component to the local controller when degraded operating modes are detected. The supervisor is built according to the satisfaction degree of the different and possible conflicting objectives quantified by fuzzy intervals.

The transition from a computed continuous control to a discrete dispatching control is performed through a sampling procedure. The principle consists to

transform the calculated production rates to time intervals by taking their inverse. Finally, in order to cope with the eventual conflicts of multiple routes, the scheduling decisions are made by using some criterion representing a measure of the priority. The proposed criterion is based on the production rates, the surplus performances and the operation order of the different products of the same machine. Comparisons through simulations show that the proposed methodology achieves the production in the shortest time (makespan) with regard to conventional schedulers.

The only uncertainty considered in this paper has been the overall objectives quantification. An important open issue is the robustness of the methodology when other forms of uncertainty are present, such as random arrival, service, setup times and random machine failures and repairs.

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