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Karim Tamani*, Reda Boukezzoula*, Georges Habchi**
*LISTIC – ESIA **SYMME – ESIA
Domaine universitaire
B.P. 806 – 74016 Annecy Cedex
email: {Karim.Tamani, Reda.Boukezzoula, Georges.Habchi}@univ-savoie.fr

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ABSTRACT

A particular characteristic of a manufacturing system concerns the complexity and the presence of uncertainties along with the difficulties in building analytical models that capture the system in all its important aspects. Hence, simulation remains one of the most widely used tools to fill this need. The objective of this article is related to the potential improvement of computer simulation as applied to the control of manufacturing system by introducing a two-level fuzzy-logic based control structure. On the lower level of the hierarchy, there is an adaptive fuzzy controller for each specific production module which is sythesized to regulate the flow of the material into a system, and in the upper level, a supervisor has the task of coordinating and tuning the local controllers by using the performance measurements characterizing the overall system's current behavior to achieve better performance and restrict the system in admissible domain.

INTRODUCTION

Modern manufacturing systems are characterized by high degree of automation and integration, low levels of work in process inventory, high capital costs, and various forms of supervisory control. While modelling and analysis are important to help ensure good system performance, the integration and complexity of systems often makes purely analytic tools difficult to use. Other difficulties come from the uncertainty inherent to data collected for control and from the necessity of interfacing with human operators.
Due to this fact, a common way to evaluate the performance of a manufacturing system (along with its control system) is through simulations. Traditionally, simulation has been used for offline decision-making. This require considerable amount of time spent in gathering and analysing data. In order to enhance the capabilities of computer simulation, the task was to find a way of introducing control into simulation by pursuing generic and applicable concepts (Berchet 2000, Habchi and Berchet 2003). In addition, human experts are the ones that, by using practical rules, make a manufacturing systems work to the desired objective. This leads to the idea of a control approach that mimics the behavior of human experts, that is the emerging field of intelligent manufacturing. The literature offers a wide variety of intelligent techniques for the control of manufacturing systems. In the context of this work, we use the fuzzy theory in the control systems to improve the simulation process. The application of fuzzy control concepts in manufacturing systems has not received much attention until recent years, mainly in the field of scheduling (Angsana and Passino 1994, Custodio et al. 1994, Dadone 1997, Yuniarto and Labib 2005). The problem that we deal is how to regulate the flow of the material into a manufacturing system consisting of a network of resources. The objective is to meet demand for finished products, while guaranteeing stability. The proposed control approach is characterized by two hierarchical levels. In the lower level, there are distributed fuzzy controllers to regulate the production flow in the system, and in the upper level, the supervisor has the task of coordinating and tuning the local controllers, using the performance measures characterizing the overall system's current behavior to achieve better performance and restrict the system in admissible domain.
The remainder of this paper is organized as follows. Section 2 introduces the conceptual approach for simulation modelling and control of manufacturing systems, its potentials and limits. In section 3, we present an adaptive fuzzy controller on which our simulation approach is based. Section 4 discusses the supervisory control strategy. In section 5, simulation results are given to illustrate the feasibility of the approach. Concluding remarks are finally given in section 6.

CONCEPTUAL APPROCH FOR MANUFACTURING SYSTEMS

In this section, we present a conceptual objects, developed in our laboratory (LISTIC), to model and simulate the resources of a manufacturing system and integrate the control processes in the simulation. Basically, a manufacturing system is divided into three subsystems: physical, informational and decisional. Nevertheless, as simulation models are based on information, we only considered two subsystems: operation and control.

The Production Processing System

In the operation subsystems, we define the Production Processing System (PPS) as a generic object having all structural and functional characteristics of a production resource (Bakalem 1996). It presents the following properties:

- It defines atoms, grouping the natural succeeding of the three fundamental operations of a resource (receiving, processing and supplying);
- It synthesises the resource and its behaviour at the same time;
- It is a recursive structure able to develop models at different levels of abstraction and hierarchy.

The first and second properties describe a PPS standard behaviour consisting in the three-function cycle: *receiving*, *processing* and *supplying*. The third property presents the different states that a PPS could have in a given simulation according to the level of detail needed in the model, and the hierarchical structure allowing the development of models at five different levels (machine, workstation, cell, work-centre, shop).

The Control Centre

In the control subsystem, we define the Control Centre (CC) as an organised and autonomous structure, depending on the company global strategy, having a decisional authority, associated with a controlled entity and having the necessary resources to apply actions and achieve the defined goals within the global framework of the company (Berchet 2000, Habchi and Berchet 2003).
The CC disposes of components: decision-makers, referents, objectives, internal information, external information, performance indicators, measures, actions, control rules, resources. The behaviour of the CC control process is driven by the crisp rules of the form:

IF the control objective given in term of threshold is not satisfied THEN apply the adequat action according to the predefined program based on the cause and effect relation

Figure 1 presents the four main steps in the CC control process:

- *PPS performance evaluation* consists in analysing the measure obtained from the PPS, comparing it with the CC objective, and then concluding if a deviation exists. The main tool used is the performance indicator (e.g., in process inventory WIP=12, WIP objective=10, WIP<WIP objective then deviation exist);
- *cause search* concerns the identification of the cause responsible for the PPS deviation. The identification is done by examining lower level performance indicators (e.g., failure rate=0.07, failure objective≤0.05, failure rate>failure objective, then the responsible cause is the failure);
- *action search* consists in the identification of the action able to correct the current deviation of the PPS and prevent future deviations. The seeking of the right action may be done with the help of cause and effect relation, and internal simulation (e.g., actions: preventive maintenance, reliability enhancing, quick repairing,. . .);
- *action applying* concerns the planning and application of actions with the help of the relevant competent resources (e.g., maintenance service).

Advantages and limits

The main advantages of modelling and simulation using the conceptual objects (PPS and CC) can be summarized in the following points:

- The reusability allowed by the generic aspect;
- The possibility of refinement considering the different levels of abstraction;
- The modular modelling property, leading the designer to consider the use of recursive structures of PPS.
- An automatic generation of the operation and control submodels according to the definition of product routings and decision-makers;
- The modelling of operation decision-making within a control process submodel based on feedback loop and performance indicators;

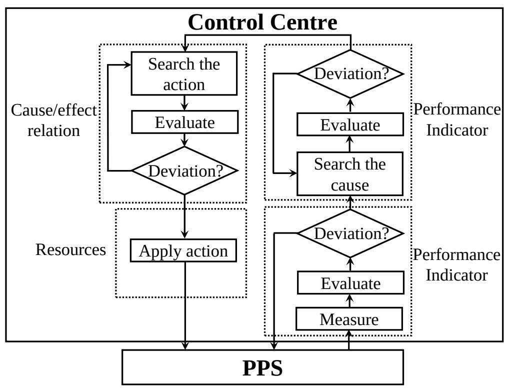

Figure 1: Main steps of the CC control process

- A clear separation between operation and control submodels.

In addition, the introduction of the control process into simulation lead to some modifications in the classical simulation process by introducing the following feedback loop – simulation, performance evaluation, action – into the simulation model. The number of simulation runs allowing system optimisation may thus be reduced. However, the current behaviour of the CC is based on crisp rules and there is no learning mechanism taking the past and present values of the performance indicators into account. Furthermore, the human experts are not exploited, and the co-ordination between the different CC are not implemented.
To overcome some of these limits, we introduce a two-level fuzzy-logic based control structure to analyse the CC.

DESIGN AN ADAPTIVE FUZZY CONTROLLER FOR A SINGLE MACHINE

In this section, we introduce an adaptive fuzzy controller in order to analyse the potential improvements of the CC. We consider the in-process inventories, widely known as Work-In-Process (WIP), as a performance measure of manufacturing system. The control objective is to satisfy the demand and keep WIP as low as possible. This is attempted by constantly regulating the production rate u_i performed at each machine M_i.
A fuzzy controller for each machine is described with the input variables:

- The levels of the upstream and downstream buffers $x_{l,i}, x_{i,k}$ ($l = 1, \ldots, L$ and $k = 1, \ldots, K$) respectively of a machine M_i;
- The production surplus s_i of M_i which is the difference between the cumulative production and demand;
- The state of the machine α_i.

Since the major control objective is to keep the error between the production and demand close to zero, we use an adaptive fuzzy controller based on the Takagi-Sugeno fuzzy model (Boukezzoula et al. 2001). The chosen approach consists in adjusting the conclusion parameter, which provides the fraction of the capacity of the machine devoted to processing.
In the case of a production module composed of a machine M_i, one upstream buffer, and one downstream buffer, the Takagi-Sugeno fuzzy rules describing the controller are:

$R^{(i_1,i_2,i_3)}$: IF $x_{i-1,i}$ is $X_1^{i_1}$ AND $x_{i,i+1}$ is $X_2^{i_2}$ AND s_i is $X_3^{i_3}$ THEN $r_i = \phi(i_1, i_2, i_3)$

where $X_p^{i_p}$ (p=1,2,3) is the i_p^{th} linguistic term associated with the vector of the input variables $x = [x_{i-1,i}\ x_{i,i+1}\ s_i]$, which are the upstream/downstream buffer levels, and the surplus, respectively, while $\phi(i_1, i_2, i_3)$ denote the real value involved in the rule conclusion. Table 1 shows the fuzzy sets defined for all the input variables. The gains are used to map the actual inputs of the fuzzy system to the normalized universe of discourses (Lee 1990).

Table 1: Linguistic term of the fuzzy sets (E=Empty, A=Almost, N=Normal, F=Full, NEG=Negative, Z=Zero, POS=Positive)

Variables	Fuzzy sets				
$x_{i-1,i}$	E	AE	N	AF	F
$x_{i,i+1}$	E	AE	N	AF	F
s_i	NEG	Z	POS		

The output generated by the fuzzy controller $0 \leq r_i \leq 1$ constantly "decides" how "fast" the machine M_i should produce. In compact form, it is given by:

$$r_i = W \cdot \Phi$$

where $W \in \mathbb{R}^N$ is the row vector composed of the truth degrees of the complete rute base with $N = 5 \times 5 \times 3$ and Φ is the parameter vector of the real values involved in the rule conclusions. The adaptation process involves the adjustment of Φ at each step so that the tracking error (i.e., surplus s) converges to zero. This is applied by using the following algorithms:

$$\Phi(t_{k+1}) = \Phi(t_k) - \eta \cdot W \cdot s_i(t_k)$$

where η is a positive constant value, and t_k denote the k^{th} discrete time point.
When the tracking error is satisfied (i.e., surplus close to zero), the controllers keep buffers regulating the machines rates at neither full nor empty (Ioannidis et al. 2004). Considering the simple case of one product with one operation, the production rate of machine M_i would be:

$$u_i(t_k) = \frac{r_i}{\tau_i} = r_i \cdot \mu_i$$

where $\mu_i = 1/\tau_i$ is the maximum rate at which machine M_i can process a part, and τ_i the processing time of M_i.
As stated in (Angsana and Passino 1994), the choice of the saturation value B (buffer sizes) for every buffer has an influence on the control performance. In the field of the fuzzy control, it defines the universes of discourse $[0, B]$ of the buffer levels. The optimal buffer sizes are assessed by building safety stocks to compensate future failures. To resolve this problem, we use an iterative approach. The parameter B is initially set to 1. A first simulation is run with this value and the maximum levels on each buffer are used as new values to normalize the B parameters for successive simulations. This procedure is repeated until the B parameters converge.

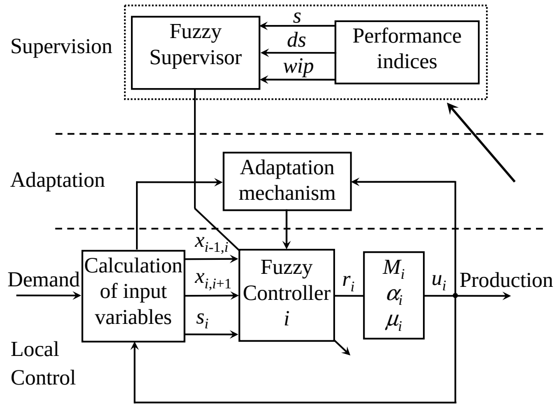

Figure 2: Supervised control structure

DESIGN OF SUPERVISORY CONTROLLER

In this section, we describe the supervisor by adapting the approach proposed in (Ioannidis et al. 2004). The objective of the supervisory controller is to restrict the system in the admissible domain of the final surplus; since the surplus is giving a more precise picture of the system's state. If it is negative, customers are not satisfied. If it is positive and has a high value, WIP is high. The supervised control structure is shown in Figure 2.
The input variables of the supervisor are:
The mean surplus of the end product (s), the error variation (ds), and the value of the mean work-in-process (wip). Both the parameters s and ds are used to keep production close to the demand, while the variable wip restrict the number of parts in processing.
The outputs of the supervisor are the correction factors $-1 \leq u_c \leq 1$ and $-1 \leq l_c \leq 1$ of the upper and lower admissible domain (surplus) bounds, respectively. These correction factors express the percentage by which the domain's bounds are altered.
The expert knowledge that describes the supervisory control objective are built on the following assumption; adaptive surplus bounds may improve the production performance and guarantee the respect of the specification given in term of the maximum allowable WIP. It can be summarized in the following statements:

If the WIP is high (low) and the final surplus is positive high (negative high), then reduce (increase) the upper (lower) bound of the admissible domain.

The above knowledge is formally represented as a fuzzy logic rule, as follows:

$R^{(k)}$: IF s is $S^{(k)}$ AND ds is $DS^{(k)}$ AND wip is $W^{(k)}$ THEN u_c is $U^{(k)}$ AND l_c is $L^{(k)}$

The crisp values of the output u_c and l_c, given by defuzzification process, are used to modify the admissible domain bounds according to the following mechanism:

$$s_l = \min\left[s_{l0}(1+l_c), s_u\right], s_u = \max\left[s_{u0}(1+u_c), s_l\right]$$

where s_{l0} and s_{u0} are the lower and upper bound of the initial domain given in the specification.

SIMULATION TESTING AND RESULTS

Our simulation approach is tested in the example of assembly line presented in (Ioannidis et al. 2004). The system under consideration consists of five machines producing one product type. The failure and repair rates are equal for all machines. The repair rates are rr_i=0,5 and the failure rates are $p_i = 0,05$. The processing times τ_i $(i = 1, \ldots, 5)$ are chosen as follows:

$$\tau_1 = 2, \tau_2 = 5, \tau_3 = 2, \tau_4 = 1, \tau_5 = 3$$

For comparison purposes, we consider the simple strategy for the CC which decrease the production rate if the inventory falls below some value, increase it if the inventory shoots above a desired value, and take no action if it remains within these values. Thus, if inventory i is desired to remain within i_1 and i_2, the crisp rules of the CC will be:

IF $i < i_1$ THEN decrease the production rate of the downstream machine
IF $i > i_2$ THEN increase the production rate of the downstream machine
IF $i_1 \leq i \leq i_2$ THEN no action

All the experiments of the fuzzy control approach have been carried out using MATLAB's FlouLib toolbox (Foulloy et al. 2006), and Simulink, while the conceptual model PPS/CC of the assembly line have been performed with the help of Apollo platform (Habchi and Berchet 2003), in which the described concepts (PPS and CC) have been implemented. The time duration of each simulation run is 10000 time units.

Comparative results for the mean work-in-process for various demand patterns are shown in Table 2 and Figure 3. In the case of the conceptual model PPS/CC, all buffer capacities are fixed to 10. In Figure 4, the evolution of the mean WIP in both cases in a simulation run of 10000 time units is presented.
The results show that the fuzzy hierarchical control system has a good performance, represented by a low WIP. This behaviour demonstrates the effectiveness of the proposed approach.

CONCLUSIONS

The main purpose of this study was to show the potential improvement of computer simulation as applied

Table 2: Results for the assembly line test case

Demand (parts/t.u.)	The CC control process	Supervised adaptive fuzzy control
	Mean WIP	Mean WIP
0,05	1,01	0,794
0,08	1,61	0,983
0,1	2,03	1,355
0,15	3,33	2,563
0,18	7,27	4,644

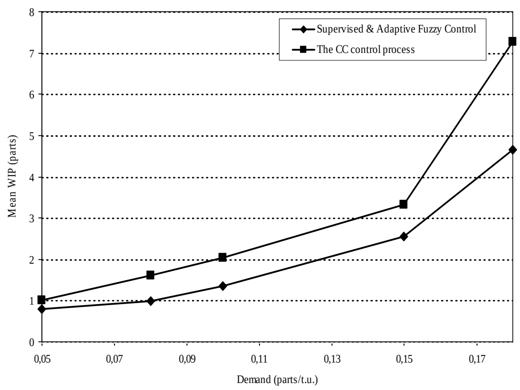

Figure 3: Comparative results of mean WIP with various demands

to the control of manufacturing system through a fuzzy formulation, which bring some intelligence in the computer simulation. Thus, we have introduced a two levels supervised control structure based on the fuzzy theory. The control is distributed, in the sense that each decision is made on the basis of only local dynamic information. So, we have introduced the supervisor that uses actual available data to characterize the overall system's current behavior and then to modify the controllers of lower level to ultimately achieve desired specification. This ensure the coordination between the distributed controllers. For the cases studied, the control algorithm leads to a low WIP compared to the CC control process. In the future work, it would be interesting to consider the case of multi-objectives, including low production lead time, high resource utilization, low tardiness, etc. This leads to multi-criteria aspects of the control. Another interesting extension would be the integration of the proposed approach in the concept of the CC.

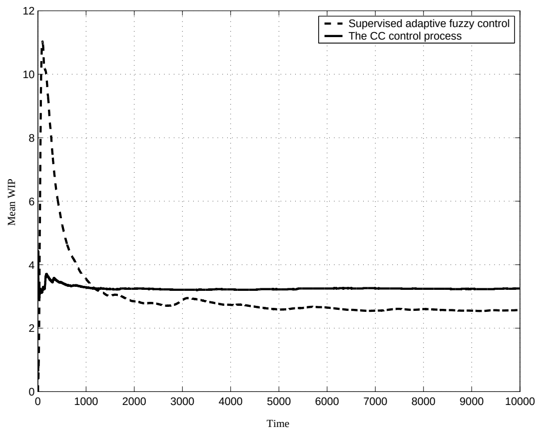

Figure 4: Evolution of mean WIP in the assembly production line with demand d=0,15

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