OPTIMIZED FUZZY SCHEDULING OF MANUFACTURING SYSTEMS

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Abstract: An Evolutionary Algorithm (EA) strategy for the optimization of generic Work-In-Process (WIP) scheduling fuzzy controllers is presented. The EA is used to tune a set of fuzzy control modules which are used for distributed and supervisory WIP scheduling. The distributed controllers objective is to control the rate in each production stage so that satisfies the demand for final products while reducing WIP within the system. The EA identifies the parameters for which the fuzzy controller performs optimal with respect to WIP and backlog minimization. The proposed strategy is compared to known heuristically tuned fuzzy control approaches. Simulation results show that the EA strategy improves system's performance.

1 INTRODUCTION

The Work-In-Process (WIP) inventory is measured by the number of unfinished parts in the buffers throughout the manufacturing system. For various reasons reported in (Conway et al, 1998) and elsewhere, the in-process inventories should stay as small as possible. The important question in WIP management is: *what is the minimum necessary WIP*? The answer, which is not straightforward, is that WIP is highly associated with the fluctuations of demand. WIP is accumulated when the actual production rate is higher than the demand. However, when WIP is very low, unpredicted phenomena, such as machine failures, may lead the actual production behind the demand and thus to delayed deliveries and unsatisfied customers. Obviously, product demands of constant level and pattern make scheduling easier than randomly changing demands.

Control policies that tend to keep WIP in low levels have drawn a great deal of attention from researchers and practitioners (Gershwin et al, 1994), (Bai et al, 1994). Recently, artificial intelligence-based methodologies for the WIP control of realistic (in terms of modelling assumptions) manufacturing systems have been presented ((Tsourveloudis et al 2000),(Ioannidis et al, 2004), (Custodio et al, 1994)).

In previous work ((Tsourveloudis et al 2000), (Ioannidis et al, 2004)), distributed and supervisory schemes for the control of WIP where introduced. In both approaches presented the controllers performed better from traditional and surplus-based policies. However, neither this approach has adopted a systematic methodology that ensures optimal design of the in – process inventory controllers.

In this paper we present an Evolutionary Algorithm (EA) strategy for optimization of generic WIP scheduling fuzzy controllers introduced in (Tsourveloudis et al 2000), (Ioannidis et al, 2004). The scheduling problem objective is to control the production rate in a way that satisfies the demand for final products while keeping minimum WIP within the production system. During the evolution, the EA identifies those set of parameters for which the fuzzy controller performs optimal with respect to WIP minimization for several demand patterns.

2 FUZZY SCHEDULING

A production system can be viewed as a network of machines and buffers. Items are received at each machine and wait for the next operation in a finite capacity buffer. The machines break down randomly and may be incapable of producing more parts because of starvation and/or blocking phenomena. Due to a failed machine with operational neighbors, the level of the downstream buffer decreases, while the upstream increases. If the repair time is big enough, then the broken machine will either block the next station or starve the previous one. This effect will propagate throughout the system.

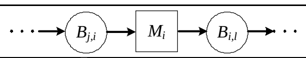
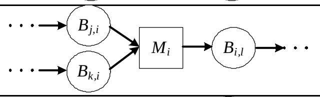
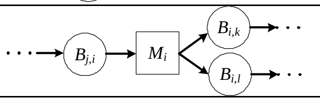
Clearly, production scheduling of realistic manufacturing plants must satisfy multiple conflicting criteria and also cope with the dynamic nature of such environments. Fuzzy logic offers the mathematical framework that allows for simple knowledge representations of the production control / scheduling principles in terms of IF-THEN rules.

Two approaches of production scheduling have been identified, the *distributed* and the *supervisory* fuzzy scheduling. The advantage of the fuzzy controllers used in the distributed approach is that computationally simple and therefore facilitate application to real time control/scheduling.

In the distributed fuzzy scheduling system presented in (Tsourveloudis et al, 2000), three basic subsystems have been introduced, namely *transfer line*, *assembly* and *disassembly* module. The majority of the real production networks can be decomposed into these subsystems. Each subsystem can be seen as a distributed fuzzy logic controller.

The inputs of the control modules (Table 1) are the buffer levels B_{ji}, B_{il}, B_{ki}, B_{ik}, B_{il}, the state s_i of the machine M_i, the production surplus x_i of M_i and the sole output is the processing rate r_i of M_i.

Table 1: Control Modules

Module	Schema
Line	
Assembly	
Disassembly	

The control objective of the distributed scheduling approach, is to satisfy the demand keep WIP as low as possible. This is attempted by regulating the processing rate r_i at every time instant. The expert knowledge that describes the control objective can be summarized as follows:

If the surplus level is satisfactory then try to prevent starving or blocking by increasing or decreasing the production rate accordingly.

If the surplus is either too low or too high then produce at maximum or zero rate respectively.

The above knowledge is formally represented, for the control modules of Table 1, by fuzzy rules. In the case of the transfer line rule has the form:

IF $b_{j,i}$ is $LB^{(k)}$ AND $b_{i,l}$ is $LB^{(k)}$ AND s_i is $LS_i^{(k)}$ AND x_i is $LX^{(k)}$ THEN r_i is $LR_i^{(k)}$

where *k* is the rule number, *i* is the number of machine or workstation, *LB* is a linguistic value of the variable *buffer level b* with term set *B*= {*Empty*, *Almost Empty*, *OK*, *Almost Full*, *Full*}, s_i denotes the state of machine *i*, which can be either 1 (operative) or 0 (stopped); consequently *S*= {0, 1}. *LX* represents the value that surplus *x* takes and it is chosen from the term set *X*= {*Negative*, *OK*, *Positive*}. The *production rate r* takes linguistic values *LR* from the term set *R*= {*Zero*, *Low*, *Almost Low*, *Normal*, *Almost High*, *High*}. The processing rate r_i of each machine at every time instant is

$$r_i' = f_{is}(b_{j,i}, b_{i,l}, x_i, s_i) = \begin{cases} 0 & if\ s_i = 0 \\ \dfrac{\sum r_i \mu_R^*(r_i)}{\sum \mu_R^*(r_i)} & if\ s_i = 1 \end{cases}, \tag{1}$$

where, $f_{is}(b_{j,i}, b_{i,l}, x_i, s_i)$ represents a fuzzy inference system ([7], [8]) that takes as inputs the level $b_{j,i}$ of the upstream buffer, the downstream buffer level $b_{i,l}$, x_i is the surplus (cumulative production minus demand) and s_i is a non fuzzy variable denoting the state of the machine, which can be either 1 (operative) or 0 (stopped). In (1), $\mu_R^*(r_i)$ is the membership function of the aggregated production rate, which is given by

$$\mu_R^*(r_i) = \max_{b_{j,i}, b_{i,l}, x_i} \min[\mu_{AND}^*(b_{j,i}, b_{i,l}, x_i), \mu_{FR^{(k)}}(b_{j,i}, b_{i,l}, x_i, r_i)], \tag{2}$$

where $\mu_{AND}^*(b_{j,i}, b_{i,l}, x_i)$ is the membership function of the conjunction of the inputs and $\mu_{FR^{(k)}}(b_{j,i}, b_{i,l}, x_i, r_i)$ is the membership function of the *k*-th activated rule. That is

$$\mu_{AND}^*(b_{j,i}, b_{i,l}, x_i) = \mu_B^*(b_{j,i}) \wedge \mu_B^*(b_{i,l}) \wedge \mu_X^*(x_i), \tag{3}$$

$$\mu_{FR^{(k)}}(b_{j,i}, b_{i,l}, x_i, r_i) = f_{\rightarrow}[\mu_{LB^{(k)}}(b_{j,i}), \mu_{LB^{(k)}}(b_{i,l}), \mu_{LX^{(k)}}(x_i), \mu_{LR^{(k)}}(r_i)], \tag{4}$$

In equations (3), (4), $\mu_B^*(b_{j,i})$ and $\mu_B^*(b_{i,l})$ are the membership functions (MFs) of the actual upstream and downstream buffer levels and $\mu_X^*(x_i)$ is the membership function of production surplus.

In the supervised fuzzy scheduling approach, the supervisory controller utilizes macroscopic data of higher hierarchies to adjust the overall system's behavior. Potentially, this may happen by modifying the lower level controllers in a way to ultimately achieve desired specifications. The supervisory controller's task, introduced in (Ioannidis et al, 2004) and its optimization discussed in the next paragraph, is the tuning of the previously presented distributed fuzzy controllers, in a way that improves certain performance measures without causing a dramatic change in the control architecture. The overall scheduling approach remains modular since the production control modules are not modified but tuned by the additional supervisory controller.

In the supervisory scheduling scheme it is assumed that the demand and the cumulative production are known. This is important for the production surplus monitoring and control and for scheduling decisions based on production surplus. The expert knowledge that describes the supervisory control objective builds on the assumption that adaptive surplus bounds may improve the production systems performance and can be summarized in the following statements:

If the upper surplus bound is reduced there is an immediate reduction of WIP.

If the upper surplus bound is increased there is an increase of WIP and the total production rate leading to a small reduction of backlog.

If the lower surplus bound is increased a substantial reduction of backlog and an increase in WIP is achieved.

If there is a reduction of lower surplus bound as a result we have a deterioration of backlog with an improvement of WIP.

Surplus bounds are decided by the output of IF-THEN rules of the following form:

IF mx_e is $LMX^{(k)}$AND e_x is $LE_x^{(k)}$ AND e_w is $LE_w^{(k)}$ THEN u_c is $LU_c^{(k)}$ AND l_c is $LL_c^{(k)}$,

where, k is the rule number, mx_e is the mean surplus of the end product, *LMX* is a linguistic value of the mx_e with term set *MX*= {*Negative Big*, *Negative Small*, *Zero*, *Positive Small*, *Positive Big*}, e_x is the error of end product surplus (the difference between surplus x_e and the lower bound of surplus), with linguistic value term set E_x= {*Negative*, *Zero*, *Positive*}. The relative deviation of *WIP* is denoted e_w and LE_w is the linguistic value chosen from the term set E_w = {*Negative*, *Zero*, *Positive*}. The upper surplus bound correction factor u_c takes linguistic values LU_c from U_c= {*Negative*, *Negative Zero*, *Zero*, *Positive Zero*, *Positive*} and the lower surplus bound correction factor l_c takes linguistic values LL_c from the term set L_c= {*Negative*, *Negative Zero*, *Zero*, *Positive Zero*, *Positive*}.

The crisp arithmetic values, u_c^* and l_c^*, of the corrections of the upper and lower surplus bounds, respectively, are given by the following defuzzification formulas:

$$u_c^* = \frac{\sum u_c \cdot \mu_{U_c}^*(u_c)}{\sum \mu_{U_c}^*(u_c)}, \text{ (5a)} \quad l_c^* = \frac{\sum l_c \cdot \mu_{L_c}^*(l_c)}{\sum \mu_{l_c}^*(u_c)}, \text{ (5b)}$$

where $\mu_{U_c}^*(u_c)$ and $\mu_{L_c}^*(l_c)$ are the MFs of the upper and lower surplus bounds, respectively. These MFs represent the aggregated outcome of the fuzzy inference procedure. The correct selection of input and output membership functions characterizes the performance of the overall scheduling task.

Since the form of the fuzzy rules of both the distributed and supervised approach for fuzzy scheduling have been identified, a crucial point is the selection of the MFs. The correct choice of the MFs is by no means trivial but plays a crucial role in the success of an application. Consequently, the selection of MFs if not based on a systematic optimization procedure cannot guarantee minimum WIP level. This is the main drawback of the heuristic selection of MFs in case of known (or almost known) demand patterns. The evolutionary algorithm developed and explained in the next section, creates MFs that fit best to scheduling objectives. In this context, the design of the fuzzy controllers (distributed or supervisory) can be regarded as an optimization problem in which the set of possible MFs constitutes the search space.

3 EVOLUTIONARY FUZZY SCHEDULING

The use of evolving genetic structures for the production scheduling problem, has recently gained a lot of acceptance for the automated and optimal design of fuzzy logic systems (Tedford et al, 2001). Here, we consider the application of an evolutionary algorithm for the optimal selection of MFs.

The MF defined in the previous paragraphs are used to construct the *chromosome*. The basic idea is to represent the complete set of MFs by an individual (chromosome) and to evolve shape and location of the MFs. This is shown in Figure 1 for the case of trapezoidal and triangular MFs. An initial population is derived from the first chromosome by repeated application of the mutation operator. The objective is to optimize a performance measure which in the EAs context is called *fitness function*. In each generation, the fitness of every chromosome is first evaluated based on the performance of the production network system which is controlled through the membership functions represented in the chromosome. A specified percentage of the better fitted chromosomes, is retained for next generation. Parents are selected repeatedly from the current chromosomes generation, and new chromosomes are generated from the parents. One generation ends when the number of chromosomes for the next generation has reached the quota. This process is repeated for a pre-selected number of generations.

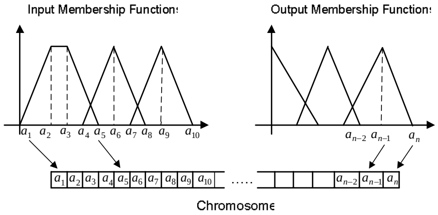


Figure 1: Chromosome created by the MFs

The structure of the distributed fuzzy logic controllers as far as it concerns the rule base and the linguistic variables remains the same with those described in Section 2. The controllers used for training have randomly created membership functions. The initial population is consisted of individuals which have the same initial chromosome which contains the points a_i, ($i=1,\ldots, n$) that define the membership functions of the inputs and the output of the controllers. In case of more than one controller the chromosome consists of the points that define all membership functions of these controllers. the membership functions, which correspond to the linguistic variables, are randomly created in the begging of the evolution process.

The evolutionary algorithm maintains a population of individuals in each generation / iteration. Individuals represent a different set of distributed fuzzy controllers. In every generation the individuals are sorted from the best to the worst based on their fitness score. As far as it concerns the fitness function, in the case of the distributed fuzzy control evolution concept, it has the following form:

$$F(x_i) = \left[\sum_{j=1}^{N} (D(t_j) - PR(t_j))^2 \right]^{-1}, \qquad (6)$$

where, t is the current simulation time, T is the total simulation time and $D(t)$ is the overall demand and $PR(t)$ is the cumulative production of the system. The architecture of the distributed evolution scheme is presented in Figure 2.

The best individual is considered the one with the biggest fitness. The fittest individuals are selected and undergo mutations. The fittest controllers and their mutated offsprings are forming the new population. After some generations the algorithm converges and the best individuals represent near optimal solutions. After the evolution process the membership functions shape is altered.

In case of the supervisory fuzzy evolutionary scheduling, the procedure is similar. In the lower control level were used the heuristic fuzzy distributed controllers introduced in (Tsourveloudis et al, 2000). The parameters were chosen as in the distributed case, that is, population number is 40 and mutation rate is 0.1. From the overall population the 20 fittest individuals are qualified for the next generation while the rest are replaced by mutation of the fittest. Each individual is evaluated by the results of a simulation run of 200 time units. The architecture of the supervisor evolution scheme is shown in Figure 3.

In the case of the fuzzy supervisory evolutionary concept the fitness function is:

$$F = \frac{1}{c_I \overline{WIP} + c_b \overline{BL}}, \qquad (7)$$

where, $\overline{WIP}$ and $\overline{BL}$ are the mean work-in-process and mean backlog, respectively. The c_I, c_b are weighting factors that represent the unit costs of inventory and backlog respectively. By taking into account these costs in the fitness function we may adjust the importance of $\overline{WIP}$ and $\overline{BL}$.

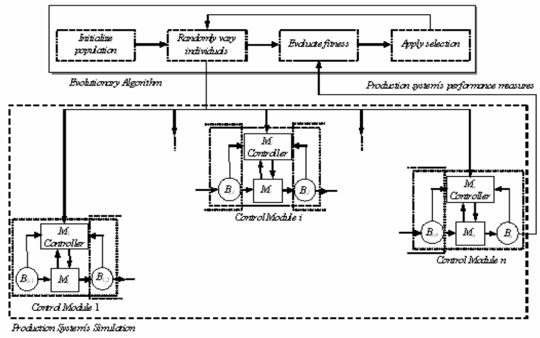


Figure 2: Distributed fuzzy evolutionary concept

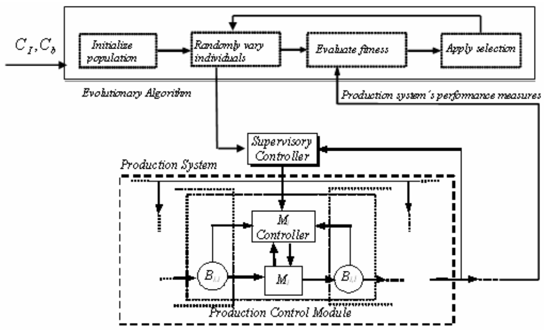


Figure 3: The fuzzy supervisory evolutionary concept

4 EXPERIMENTAL RESULTS

We have used the evolutionary algorithm presented to optimize the performance of the unsupervised / distributed and the supervised production control schemes. The evolutionary fuzzy approaches are tested and compared with the heuristic approaches introduced in (Tsourveloudis et al, 2000), (Ioannidis et al, 2004). We assume continuous parts flow within the system. In the continuous-flow simulation the discrete production is approximated by the production of a liquid item (Kouikoglou et al, 1997).

Several assumptions were made for all simulations. Machines fail randomly with a failure rate p_i and are repaired randomly with rate rr_i. Unlimited repair personnel is assumed. Time to failure and time to repair are exponentially distributed. Demand is either constant or stochastic with rate d. In stochastic case it follows the Poisson distribution. Machines operate at known, but not necessarily equal rates. Each machine produces in a rate $r_i \leq \mu_i$, where μ_i is the maximum processing rate of machine M_i. The initial buffers are infinite sources of raw material and so the initial machines are never starved. Buffers between adjacent machines M_i, M_j have finite capacities. Set-up times or transportation times are negligible or are included in the processing times.

In order to test both the distributed and the supervised evolutionary fuzzy approach the systems presented in figures 4, 5 were used.

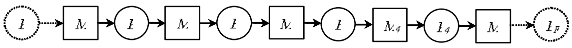


Figure 4: Production line

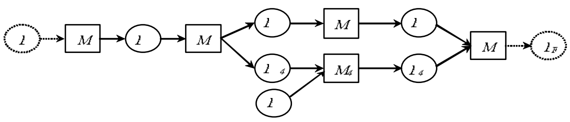


Figure 5: Production Network

4.1 Distributed evolutionary fuzzy approach

Several scenarios have been studied for the case of the Evolutionary Distributed Fuzzy (EDF) approach and the results were compared with the ones produced from the Heuristic Distributed Fuzzy approach (HDF).

For the case of the production line, 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 = 0.1. The processing rates are also equal for all machines and are equal to μ_i = 2 (i=1,...,5).

In Figure 6 the evolution $\overline{WIP}$ for both evolutionary and heuristic systems in a simulation run of 10000 time units is presented.

Comparative results for the $\overline{WIP}$ and $\overline{BL}$ for various demand patterns are shown in Table 2. All buffer capacities are equal to BC_i = 10.

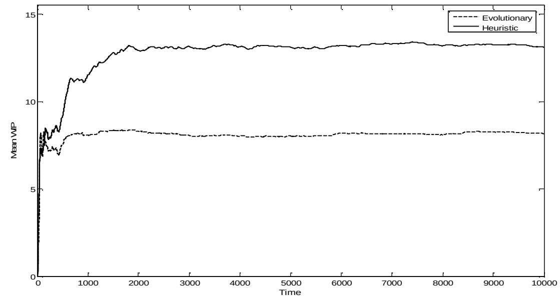


Figure 6: Evolution of $\overline{WIP}$ in the production line with stochastic demand (d = 1)

In Figure 7 the evolution of mean backlog $\overline{BL}$ for the same case is presented.

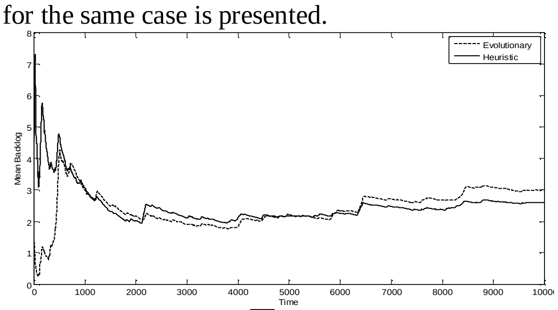


Figure 7: Evolution of $\overline{BL}$ in the production line with stochastic demand (d = 1)

The production cost consists of inventory and backlog costs. Inventory costs are due to the capital invested for the purchase of raw material and the handling of material during the production process. It is assumed that inventory cost is independent from the stage of process. Thus, the mean production cost C is given by:

$$C = c_I \overline{WIP} + c_b \overline{BL}, \quad (8)$$

where c_I, c_b are the unit costs of inventory and backlog respectively.

The cost analysis results for the production line examined in test case for stochastic demand are presented in Table 3, where the production cost of the EDF control approach is compared with the HDF approach for various values of c_I and c_b. The distributed approach was also tested in the production network presented in Figure 6. The production system under consideration consists of five machines producing one part type. The failure and repair rates of all machines are equal. The repair rates are rr_i= 0.5 and the failure rates are p_i = 0.1. The processing rates are also equal for all machines and are equal to μ_i = 5 (i=1,...,5). All buffer capacities are equal to BC_i = 10. Comparative results for the $\overline{WIP}$ and $\overline{BL}$ for various demand patterns are shown in Table 4.

Table 2: Results for the test case of the production line

Demand		HDF		EDF	
		$\overline{WIP}$	$\overline{BL}$	$\overline{WIP}$	$\overline{BL}$
Constant	1	11.492	1.72	6.371	1.567
Stochastic	0.5	19.393	0.057	6.417	0.438
	1	12.719	2.496	8.07	2.427

Table 3: Cost analysis

Demand	c_I	c_b	Cost C	
			HDF	EDF
0.5	0.99	0.01	19.2	6.357
	0.75	0.25	14.56	4.922
	0.5	0.5	9.725	3.428
	0.25	0.75	4.891	1.933
	0.01	0.99	0.25	0.498
1	0.99	0.01	12.617	8.014
	0.75	0.25	10.163	6.659
	0.5	0.5	7.608	5.249
	0.25	0.75	5.052	3.834
	0.01	0.99	2.598	2.483

Table 4: Results for the production network test case

Demand		HDF		EDF	
		$\overline{WIP}$	$\overline{BL}$	$\overline{WIP}$	$\overline{BL}$
Constant	1	21.356	0.078	16.542	0.737
Stochastic	0.5	20.097	0.049	17.34	0.136
	1	20.496	0.087	10.046	0.673

4.2 Supervised fuzzy evolutionary approach

The Evolutionary Supervised Fuzzy approach (ESF) was tested in the case of the production line of the Figure 4 and was compared with the Heuristic Supervised Fuzzy approach. Comparative results for the $\overline{WIP}$, $\overline{BL}$ and production cost C, when c_I and c_b are equal to 0.5, for various stochastic demand patterns are shown in Table 5. The supervised approach was also tested in the production network presented in Figure 5. Table 6 shows comparative results of $\overline{WIP}$, $\overline{BL}$ and C, when c_I and c_b are equal to 0.5, for various stochastic demand patterns.

Table 5: Comparative results for the test case of the production line

Demand	HSF			ESF		
	$\overline{WIP}$	$\overline{BL}$	C	$\overline{WIP}$	$\overline{BL}$	C
0.5	19.886	0.167	10.027	6.446	0.32	3.383
1	0.5	2.584	7.153	9.17	3.853	6.512

Table 6: Results for the production network test case

Demand	HSF			ESF		
	$\overline{WIP}$	$\overline{BL}$	C	$\overline{WIP}$	$\overline{BL}$	C
0.5	5.43	0.09	2.76	1.406	1.888	1.647
1	7.162	0.505	3.834	3.036	2.681	2.859
2	14.55	2.777	8.666	8.914	5.55	7.232

5 CONCLUSIONS

An evolutionary algorithm strategy for the optimization of already established fuzzy production control architectures ((Tsourveloudis et al, 2000), (Ioannidis et al, 2004)) has been presented. The EA strategy selects the membership functions of the fuzzy controllers in a way that WIP and backlog values minimize fitness function based on production surplus. Simulation results, for a number of taste cases, have shown an important improvement of performance and production related costs, with the use of EA strategies. More specifically the EA strategies manage to reduce substantially the weighted sum of WIP and backlog and thus improving the inventory and backlog costs. Evolutionary algorithms clearly represent a successful approach towards the optimization of fuzzy production control approaches.

In the future it would be very interesting to consider the case of seasonal demand. Another interesting extension would be the use of EA strategies in more complex production systems such as multiple-part-type and/or re-entrant systems.

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REFERENCES

Bai SX and Gershwin SB, (1994). Scheduling manufacturing systems with work-in-process inventory control: multiple-part-type systems. *In Int J Prod Res*, 32:365-386.

Conway R, Maxwell W, McClain JO, Joseph Thomas L, (1988) .The role of work-in-process inventory control: single-part-systems. *In Oper Res*, 36:229-241.

Custodio L, Sentieiro J, Bispo C, (1994) Production planning and scheduling using a fuzzy decision system..*In IEEE Trans Robot Automat*, 10:160-168.

Gershwin SB (1994) *Manufacturing Systems Engineering*, Prentice Hall, New Jersey.

Ioannidis S, Tsourveloudis N, Valavanis K, (2004) Fuzzy Supervisory Control of Manufacturing Systems. *In IEEE Trans Robot Automat*, 20:379-389.

Kouikoglou VS and Phillis YA, (1997). A Continuous-flow Model for Production Networks with Finite Buffers, Unreliable Machines, and Multiple Products. *In Int J Prod Res*, 35:381-397.

Tedford JD and Lowe C, (2003) Production scheduling using adaptable fuzzy logic with genetic algorithms. *In Int J Prod Res*, 41:2681–2697.

Tsourveloudis NC, Dretoulakis E, Ioannidis S, (2000) Fuzzy work-in-process inventory conntrol of unreliable manufacturing systems. *In Inf Sci*, 127:69-83.