MODELING AND SIMULATION OF GENETIC SUPERVISORY FUZZY CONTROLLERS FOR MULTI-PART-TYPE PRODUCTION LINE

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ABSTRACT

Genetic supervisory fuzzy (GSF) control architecture for multi-part-type production line is proposed. More than one part type can be processed by each machine in such production systems. GSF control architecture composed of two layer controller. In first layer heuristic distributed fuzzy (HDF) controllers control each machine separately, while GSF controllers used in second layer. GSF controllers tune the decisions made by HDF controllers, based on overall conditions of production system. Genetic algorithm (GA) is used to adapt the membership functions of supervisory fuzzy controllers, to improve the performance of GSF controllers. The overall objective is to control the production rate in a way that satisfies the demand for final products while keeping minimum work-in-process (WIP) and backlog within the production system. GA is used to minimize costs of WIP and backlog. The GSF control architecture is tested and compared with the heuristic supervisory fuzzy (HSF) controllers. The results show that in most of the cases GSF outperform the conventional supervisory controllers.

Keywords: *genetic algorithm, fuzzy controller, genetic fuzzy systems, multi-part-type production line.*

INTRODUCTION

Globalization, higher customers' awareness, new communication gate ways and global competition forced manufacturing to decrease the wastes and increase their performances. Customers are seeking for lower prices and better qualities, even zero defects. In this situation if one company neglects of improving itself, there are lots of competitors to do it, and increase their market share. The focal point in the conversion of materials into finished products is production control. A set of on time decisions for various production statuses should be made by control systems. Improving the effectiveness of production control systems cause improvement in scheduling of production systems. Production scheduling manages the flow of materials or components through the manufacturing system [1]. The procedure of control system is quite simple. The system state is mapped onto a set of possible control actions. State variables define the system state. These variables determine the overall specifications of the manufacturing system in each time period. This information consists of number of part types, inventories in hand, and the status of a machine and so on. Control actions are responsible to change the system state in order to satisfy the overall goal of system. The method of mapping the system state to control action usually been created on a human observation and experience basis [2]. According to Gershwin [3], surplus-based control policy is the most interested control policy in the literatures. In surplus-based systems decisions are made on the basis of how far the cumulative production is ahead of or behind the cumulative demand.

Buffers are temporary storage places for storing in-process work pieces. Usually buffers are used in multi-machine systems to smooth the production flow and reduce the negative effects brought about by machine failures. Each machine at least has two buffers (upstream and downstream), where the WIP inventories stored there. When the downstream buffer is full and there is no more room for another part, blockage happens. Starvation happens when upstream buffer is empty and there is no more part to process by machine M_i. If the starvation or blockage statuses continue for a substantial time period, these situations can propagate from one machine into all of the production system. Usually production networks are controlled base on work-in-process (WIP) level and capacity of buffers, and their main objective is to avoid both starvation and blockage.

In this paper genetic supervisory fuzzy (GSF) control system [1 and 4] is developed for multi-part-type production line. The genetic algorithm (GA) [5] is implemented to optimize the performance of WIP fuzzy controllers. GA is a robust optimization tool which is used in complex optimization problems and follows the natural evolution. The main objective of control problems 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 GA optimizes the membership function (MFs) of GSF controllers in a way that the overall production cost based on WIP and backlog costs minimizes. The overall methodology is to develop GA module for tuning the MFs of GSF controllers, designing the fuzzy controllers and modelling the production system using simulation software (*Simulink*®). Running the simulated model of production system is required even in practical experiments. After evolving the fuzzy controllers, one can implement them in real control systems. Beside of evaluating the performance of the proposed control system; this paper provides basic model for multi-part-type production lines. Figure 1 shows the main framework of this methodology.

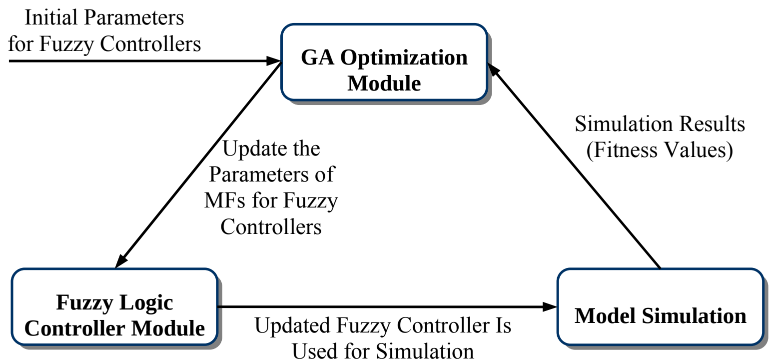

Figure 1: Main framework of GSF

LITERATURE REVIEW

Bang-bang is the classical approach for production control which says produce as much as possible when the machines are operational (up, not blocked and not starved) [6]. This control policy has only one rule. Sharifnia [7] discussed about a surplus-based production control system of a single-product system with arbitrary number of machine states. He found a production control policy that meets the demand for the product with minimum average inventory or backlog cost. The optimal production policy has a special structure and is called a hedging point policy. Moreover, Bai and Gershwin [8, 9] proposed their method based on the determination of a desirable production surplus value, or the hedging point. The control laws used are summarized in the following:

1. If the actual surplus is less than the hedging point, then machine should produce at its maximum rate,
2. If surplus is equal to the hedging point, then the production rate should be equal to demand,
3. If surplus is greater than the hedging point, then stop producing.

Bai and Gershwin [8 and 9] developed a real time feedback control algorithm for scheduling single-part-type production lines. Moreover, Bai and Gershwin considered scheduling problem for multi-part-type flow shops [10]. Song and Sun [11] studied a single part production system with exponentially distributed processing time. The demand arrival was assumed to describe by a Poisson process. It is shown that the optimal policy is of a hedging point structure. Some relations between hedging point level and system properties were considered in this research. Tedford and Lowe [12] proposed an order release mechanism incorporating an adaptable fuzzy logic controller (FLC) [2] which was tuned by genetic algorithms. Through the use of fuzzy logic, the system can consider multiple criteria and rapidly determine solutions of consistently high quality.

Mok and Porter [13] presented an evolutionary stochastic optimization procedure to estimate the short-run optimal hedging points for failure-prone production systems under crisp-logic control. The relative merits of genetic algorithms, evolution strategies, and adaptive evolution strategies have been compared in the optimization of hedging points for unreliable production systems. Chan et al. [14] proposed a mathematical model for production control problem in a manufacturing system with time delay, demand uncertainty and extra capacity. The main objective is to minimize the mean costs for WIP inventory and occupation of extra production capacity. To solve the problem, a two level hedging point control method is proposed.

Heuristic Distributed Fuzzy (HDF) Controllers

Tsourveloudis et al. [6] developed HDF control architecture which is one the basic fuzzy controllers used in current paper. The HDF controller was applied for single and multiple part type production lines and networks with finite buffers and unreliable machines. The overall control objective is to keep the WIP as low as possible, and concurrently to maintain high machine utilization and throughput. These controller modules control the production rate in each production stage (i.e. machines) in a way that extreme events of idle periods due to machine starvation or blockage are eliminated. These controllers were called distributed fuzzy controllers, because the control modules are distributed in production processes and control each machine separately. As illustrated in figure 2, each control module is connected to its preceding ($B_{j,i}$) and following ($B_{i,l}$) control stations, through joint-controlled upstream and downstream buffers.

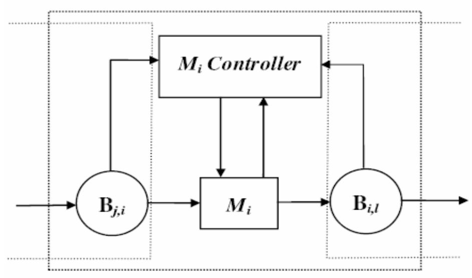

Figure 2: Distributed fuzzy controller [6]

In HDF control system, each machine or workstation is a subsystem. Inputs for the controlling module are:

1. Level of WIP in the adjacent upstream and downstream buffer(s),
2. State of machine i (down or up),
3. The production surplus of machine i.

The output of control module is the production rate for machine M_i. There are two rules to control the machines:

- If there is no sign of machine starving or blockage, then keep the production surplus close to zero,
- If an undesirable event (starvation or blockage) is about to occur, then ignore surplus levels and try to prevent starving or blockage by increasing or decreasing the production rate accordingly.

These two main rules can be expressed as a fuzzy rule:

$$\text{IF } b_{j,i} \text{ is } LB^{(k)} \text{ AND } b_{i,l} \text{ is } LB^{(k)} \text{ AND } ms_i \text{ is } LMS_i^{(k)} \text{ AND } x_i \text{ is } LX^{(k)} \text{ THEN } r_i \text{ is } LR_i^{(k)} \quad (1)$$

The k is the rule number (k = 1; . . . ; 18), i is the number of machines or workstations, LB is a linguistic value of the variable buffer level b with term set B= *{Empty; Almost Empty; OK; Almost Full; Full}*; ms_i denotes state of machine i, which can be either 1 (operative) or 0 (stopped) and consequently $MS = \{0; 1\}$. LX represents value of surplus x, 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; Normal; High}*.

Heuristic Supervisory Fuzzy (HSF) Controllers

To tune the performance of HDF controllers, Ioannidis et al. [15] developed HSF controller for production systems. The overall production control system was viewed as a two level surplus-based control system. Therefore, the overall scheduling approach remains modular since the production control modules are not modified but simply tuned by the additional supervisory controller. In HSF control architecture the performance of lower level controllers are modified or tuned to maintain desirable specification. HSF controller restricts decisions made by HDF controllers, when they are injurious for overall performance of production system. Each production system has as many HSF controllers as its product type numbers.

The objectives were to keep the WIP and cycle time as low as possible maintaining at the same time quality of service by keeping backlog at low levels. The production rate in each production stage was controlled to satisfy demand, avoid overloading and eliminate machine starvation or blockage. The supervisory control architecture is shown in figure 3. The input variables of the supervisory controllers are:

1. The mean surplus of the end product mxe,
2. The difference between the end product surplus xe and the initial lower bound of surplus I_l ,
3. The relative WIP error ew which is

$$ew = \frac{WIP(t) - \overline{WIP}(t)}{\overline{WIP}(t)} \quad (2)$$

where $\overline{WIP}(t)$ is the mean WIP (included the end product buffer level) of the production system until time t. Relative WIP error ew is used as a measure of WIP performance. Since an analytical measure of the optimal mean WIP cannot be assessed, $\overline{WIP}(t)$ is used as a target value. In HSF control architecture it is assumed that defining surplus bounds may improve overall performance of production control system. The expert knowledge which describes the objective of HSF controllers can be summarized in the following statements [16]:

- If the upper surplus bound is reduced there is an immediate reduction of WIP.
- If the upper surplus bound is increased there are 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 a deterioration of backlog with an improvement of WIP is happened.

The rule base of the supervisory controller contains rules of the following form:

$$\text{IF } mx_e \text{ is } LMX^{(k)} \text{ AND } e_x \text{ is } LE_x^{(k)} \text{ AND } e_w \text{ is } LE_w^{(k)} \text{ THEN } u_c \text{ is } LU_c^{(k)} \text{ AND } l_c \text{ is } LL_c^{(k)} \quad (3)$$

where, k is the rule number (k=1,…,29), LMX is a linguistic value of the variable *mean end product surplus* with term set MX ={*Negative Big*, *Negative Small*, *Zero*, *Positive Small*, *Positive Big*}, ex denotes the *error of end product surplus* which is the difference between surplus x and the lower bound of surplus, the term set of the corresponding linguistic value is EX = {*Negative, Zero, Positive*}. LE_w represents the relative deviation of WIP from its mean value, and it is chosen from the term set E_w={*Negative, Zero, Positive*}. The *upper surplus bound correction factor* takes linguistic values LU_c from the term set U_c = {*Negative, Negative Zero, Zero*, *Positive Zero*, *Positive*} and the *lower surplus bound correction factor* takes linguistic values LL_c from the term set L_c = {*Negative, Negative Zero, Zero*, *Positive Zero*, *Positive*}.

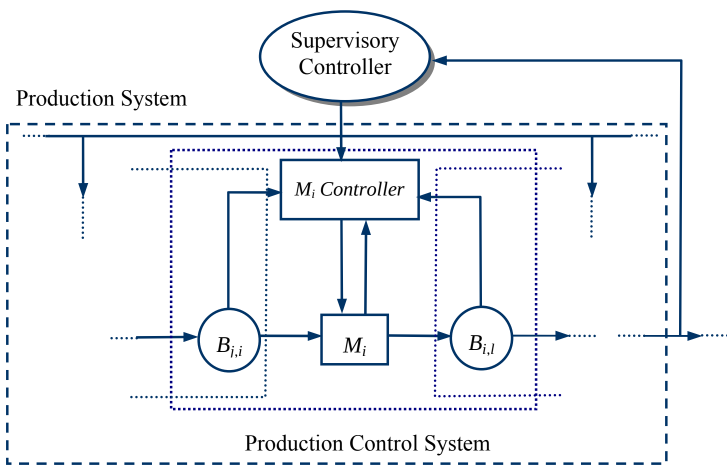

Figure 3: Supervisory fuzzy control architecture [15]

The supervisory controller output variables are the production surplus upper and lower bound correction factors (u_c and l_c), where $-1\leq l_c, u_c \leq 1$. Production surplus is divided into three areas. If the surplus is lower than a lower surplus bound l_b, then machine produces at maximum rate. If the surplus is above the upper bound u_b then production is stopped. In case where surplus is between these bounds the production rate is decided in relation with the adjacent buffer levels and machine state. The production surplus bounds are modified according to the following mechanism:

$$\begin{aligned} u_b &= I_u + u_c n_u + \min(x_e, 0) \\ l_b &= \min[(I_l + l_c n_l), u_b] \end{aligned} \quad (4)$$

where I_u and I_l are the initial upper and lower surplus bounds respectively, n_u, n_l are constants chosen in such a way that l_b will never exceed u_b when x_e is positive.

GENETIC SUPERVISORY FUZZY CONTROLLER

FLCs can be considered as knowledge-based systems, incorporating human knowledge into their “knowledge base” (KB) through fuzzy rules and fuzzy membership functions [17]. Most of the conventional methods in designing KBs were focused on obtaining the expert experiences from the human operators. In the absence of such knowledge, commonly trial and error is used to reach the desired performance of system. If the number of decision variables or system status is too large this approach is not practical. In this case tuning or learning process is more useful. Genetic algorithm (GA) [5] is one of the tools in learning process [18]. Genetic fuzzy logic controllers (GFLCs) were introduced as one of the most interested kind of optimized FLCs. In GFLCs one can consider to optimize different components of KB. In this paper optimization of MFs of input variables for HSF controllers are considered. This is addressed as GSF control system. The efficiency of HSF highly depends on accuracy of their MFs. Consequently, the selection of MFs, if not based on a systematic optimization procedure, cannot guarantee a minimum WIP level. This is the main drawback of the heuristic selection of MFs in case of known demand patterns. GA creates MFs that fit best to scheduling objectives. To design GSF control systems, a set of possible MFs are considered as the search space and initial population.

Tsourveloudis et al. [1 and 4] proposed the application of GAs for the optimal selection of MFs in single-part-type production systems. As it is shown in figure 4, a "chromosome" is constructed by using the initial definition of MFs for all of the input variables [19]. For GSF controllers as it is appeared earlier there are three input variables. Theses input variables has 11 MFs entirely. MFs are selected to be in "trapezoidal" shape which has four critical parameters (a, b, c, d). Hence 44 variables can define all of the input variables for GSF controller. Figure 4 shows a sample chromosome for GSF controller. The objective of GA is to evolve shape and location of the MFs in order to increase their performance. The "initial population" is created from the first chromosome by repeated application of the "mutation" operator. The population size is selected to be 40. Mutation rate is selected to be 15%. In each generation, a series of new chromosomes is created by three-point "crossover" and mutation operators. The fittest individual of each generation is transferred to next generation directly due to elitism operator. These chromosomes are ranked based on their fitness (in this case the fitness function is performance of control system). 20 fittest chromosomes are retained for being parents of next generation. The parents and new children (offspring) formed new population. The generation is continued for 100 times. The objective function for GSF controller is defined as:

$$F = C_I \overline{WIP} + C_b \overline{BL} \tag{5}$$

where, $\overline{WIP}$ is the mean of work-in-process and $\overline{BL}$ is the mean of backlog. C_I and C_b represent the unit costs of inventory and backlog, respectively. The vital importance of $\overline{WIP}$ and $\overline{BL}$ is shown in this control system, by using their unit costs in the fitness function. In this methodology the GA module calls the GSF construction module, which is in charge of converting each chromosome into its equivalent GSF controllers. Then the production system model simulation which is described in next section is run. In this simulation GSFs are used to control the system. Finally the objective function based on the results of simulation is calculated and transferred to GA module. GA uses this objective function value to rank the chromosomes and continue its rout.

Variable name	*MX*									
Gene number	1	2	3	4	5	6	7	8	9	10
Gene value	0.000	0.100	0.190	0.305	0.200	0.290	0.380	0.490	0.390	0.480
MF parameter	$a_{1,1}$	$b_{1,1}$	$c_{1,1}$	$d_{1,1}$	$a_{1,2}$	$b_{1,2}$	$c_{1,2}$	$d_{1,2}$	$a_{1,3}$	$b_{1,3}$
Variable name	*MX*									
Gene number	11	12	13	14	15	16	17	18	19	20
Gene value	0.570	0.660	0.580	0.650	0.730	0.800	0.750	0.830	0.920	1.000
MF parameter	$c_{1,3}$	$d_{1,3}$	$a_{1,4}$	$b_{1,4}$	$c_{1,4}$	$d_{1,4}$	$a_{1,5}$	$b_{1,5}$	$c_{1,5}$	$d_{1,5}$
Variable name	*EX*									
Gene number	21	22	23	24	25	26	27	28	29	30
Gene value	0.000	0.150	0.280	0.420	0.310	0.440	0.560	0.730	0.600	0.730
MF parameter	$a_{2,1}$	$b_{2,1}$	$c_{2,1}$	$d_{2,1}$	$a_{2,2}$	$b_{2,2}$	$c_{2,2}$	$d_{2,2}$	$a_{2,3}$	$b_{2,3}$
Variable name	*EX*		*EW*							
Gene number	31	32	33	34	35	36	37	38	39	40
Gene value	0.850	1.100	0.000	0.140	0.260	0.400	0.290	0.430	0.550	0.720
MF parameter	$c_{2,3}$	$d_{2,3}$	$a_{3,1}$	$b_{3,1}$	$c_{3,1}$	$d_{3,1}$	$a_{3,2}$	$b_{3,2}$	$c_{3,2}$	$d_{3,2}$
Variable name	*EW*									
Gene number	41	42	43	44						
Gene value	0.590	0.720	0.850	1.200						
MF parameter	$a_{3,3}$	$b_{3,3}$	$c_{3,3}$	$d_{3,3}$						

Figure 4: Chromosome created by the MFs for GSF controller

To evaluate the performance of GSF controller one need to simulate the desired production system. In this paper the multi-part-type production line is considered. Bai and Gershwin [9] introduced a new approach for controlling multi-part-type production systems. Machines are virtually divided into several sub machines, based on the number of product types. Figure 5 illustrate this configuration for two-part-type production line. Controllers for each machine regulate the operation on each part type. There is a special buffer for each part type. This configuration simplifies multi-part-type production line into multiple single-part-type production lines. The structure for GSF control system for two-part-type production line is shown in figure 5. HDF controllers are used for the lower level controlling. It should be noted that the key point of GSF controller in multi-part-type production systems is that each part-type has its own performance indices. Thus each part-type need to be controlled by a GSF controller separately. In GSF control architecture the number of initial population and hence the number of GSF controllers is equal to number of part types. All of these GSF controllers need to be evaluated simultaneously. Thus the GSF controller in fact is a multi-population optimization problem.

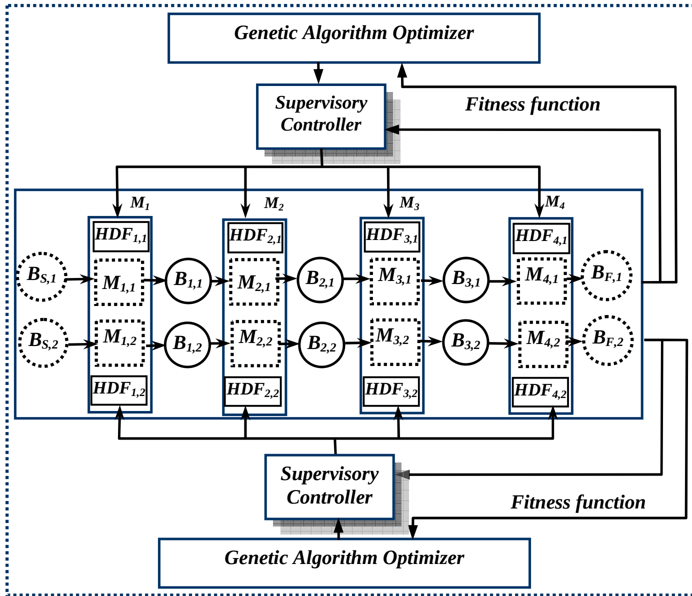

Figure 5: Multi-part-type production system and GSF controllers for it.

MODELLING & SIMULATION RESULTS

GSF controllers are implemented for multi-part-type production system. Based on the structure of the GSF control system for a multi-part-type production system (see figure 5), the main level for simulating the production system consists of two main boxes. The first box is the supervisory controller and the second box is the production system box. Figure 6 illustrates the content of production control system box. The production system box contains machine subsystems, WIP statistics boxes, and surplus and backlog statistics boxes. HDF controllers are used inside each machine block to determine the production rate of each machine.

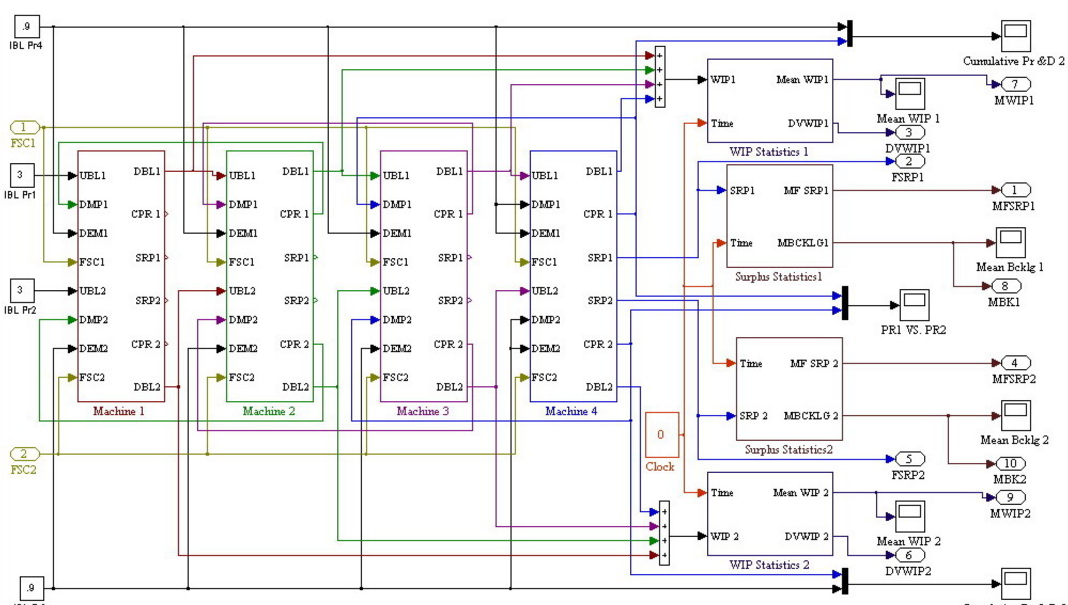

Figure 6: Two-part-type production subsystem model for Simulink®

The proposed GSF approach is tested and compared with the heuristic approaches introduced in [15]. As it is obvious in figures 5 and 6 the production system consists from four different machines which are processing two different part types. The assumptions (the same as assumption of [15]) made for all simulations are stated in following:

1. Machines fail and are repaired randomly with a failure rate of 0.5,
2. Time to failure and time to repair are exponentially distributed, Demand is constant and known with rate $d_{i,}$
3. The processing time for each part type at each machine is 0.325,
4. Each machine produces in a rate $r_i \le \mu_i$, where μ_i is the maximum processing rate of machine $M_{i,}$
5. The initial buffers are infinite sources of raw material and consequently the initial machines are never starved,
6. Buffers between adjacent machines M_i and M_j have finite capacities,
7. Setup times or transportation times are negligible or are included in the processing times.

The performance of the GSF control system for multi-part-type production system is compared with the HSF control scheme. The results of WIP level for product part type 1 with various demands (parts per time unit) and various buffer capacities are shown in figure 7.

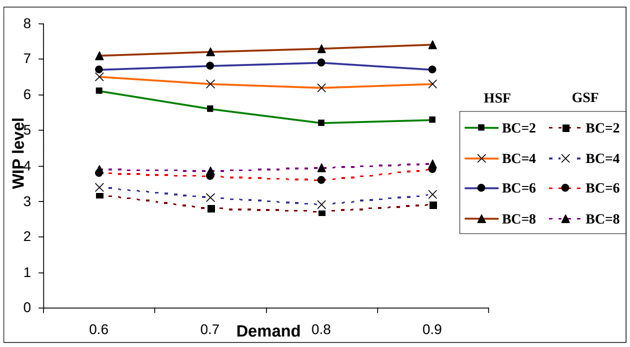

Figure 7: WIP level for various buffer capacities for product part type 1

Figure 8 illustrates the WIP level for various demands and various rates of failure. Both of these graphs show that GSF control system generally has better performance than HSF control system. The other result is that various buffer capacities and failure rates have no meaningful effect on WIP level in this test case. Table 1 compares total costs for GSF and HSF control systems, for various WIP and backlog unit costs. It shows a significant improvement in most of the cases. The overall cost of production is the same as fitness function for the test case. As it is expected, GA can improve the performance of HSF controllers. The results show that a significant reduction of WIP can be obtained through using GA to optimize MFs acquired from the experts. Based on results presented in table 1, one may observe that when the unit cost of holding WIP is small and backlog cost is much greater, then the differences between HSF and GSF are not meaningful.

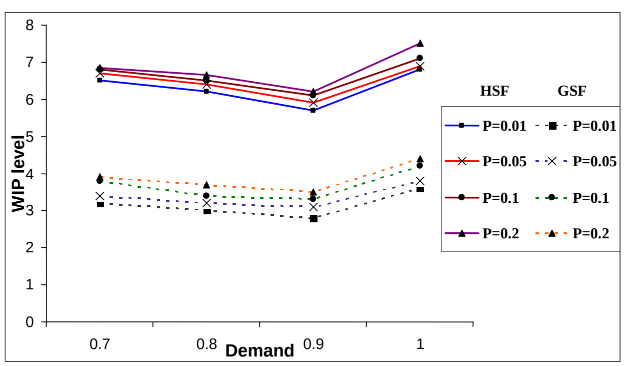

Figure 8: WIP level for various failure rates for product part type 1

WIP and backlog are two measures of the manufacturing system. If one would like to reduce the backlog level, the yield of the system has to be increased. Therefore the WIP inside the production system will be increased. The backlog level is at low level when the demand can be easily satisfied; in these cases a noticeable decrease of

WIP is more important than a small increase in backlog level. The backlog is more important in cases that demand is high, in these cases the backlog level is maintain at low levels and therefore WIP level will be increased. In most cases using GA will decrease the sum of WIP and backlog. This may be seen more clearly in the results of the production cost analysis. Generally the GSF approach outperforms the HSF scheme.

Table 1: Cost analysis for various demands and WIP and backlog unit costs

Demand	C_I	C_b	HSF			GSF		
			$\overline{WIP}$	$\overline{BL}$	C	$\overline{WIP}$	$\overline{BL}$	C
0.5	0.75	0.25	5.54	1.56	4.55	3.67	1.12	3.03
	0.5	0.5	6.91	0.57	3.74	2.73	0.34	1.53
	0.25	0.75	7.34	0.15	1.94	3.24	0.1	0.89
1	0.75	0.25	5.71	3.34	5.12	3.57	4.43	3.78
	0.75	0.25	7.14	1.52	4.33	4.32	1.59	2.96
	0.25	0.75	8.71	0.32	2.42	5.61	0.41	1.71

CONCLUSION

GSF control system for multi-part-type production systems has been presented. The GA selects the membership functions for the fuzzy controllers to minimize the amount of WIP and backlog simultaneously. The test case is a two-part-type production line with 4 machines and 2 product type. The simulation results show a significant improvement in the performance of supervisory controlling system with the use of GA strategies. Since the fitness function for the GA is a contribution of mean WIP and mean backlog levels, the results show that based on the importance of each WIP or backlog, one may decide to use GSF or HSF control system. When the backlog cost is much more than WIP holding costs it is easier to use HSF rather than GSF, because GSF need to be simulated to find the optimal MFs while HSF can be used without any simulations. Nevertheless, it is obvious that the GA shows its efficiency for choosing the MFs of fuzzy controlling system by improving the overall performance of the production system. For further researches one may consider the other patterns for demand (such as seasonal demand) or more complicated production systems. Other optimization methods also can be considered for next researches in this area.

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