Modeling and Simulation of Genetic Fuzzy Logic Controllers for Multi-Part-Type Production Line

S.M. Homayouni  S.H. Tang  N. Ismail  M.H.M.A. Megat  R. Samin
Department of Mechanical & Manufacturing Engineering, Engineering Faculty, University Putra Malaysia, Selangor, Malaysia

Abstract - Genetic fuzzy logic controlling (GFLC) system for multi-part-type production line is proposed. Genetic algorithm (GA) is used to tune membership functions of fuzzy controlling modules, to improve the performance of fuzzy controllers. The heuristic distributed and supervisory fuzzy controlling systems were used to control the production rate in a way that satisfies the demand for final products while keeping minimum work-in-process (WIP) within the production system. GA is used to minimize costs of WIP and backlog. In this paper the authors consider genetic supervisory fuzzy (GSF) controlling architecture. The GSF controlling approach is tested and compared with the heuristic fuzzy controllers. The results show that in most of the cases GSF can outperform the conventional supervisory with heuristic distributed fuzzy controlling structures.

Keywords: Genetic Algorithm, Fuzzy Controller, Genetic Fuzzy Systems, Multi-Part-Type Production Line.

1 Introduction

Manufacturing industries are one of the few ways for creating wealth in each country and have a great role in economic conditions of countries. In most of the developed and developing countries 15 to 30 percent of gross domestic production (GDP) is produced by manufacturing industries [1]. Controlling of production processes is critical for manufacturing systems. Such controlling systems involve a series of on time scheduling decisions with regard to all of the possible statuses of production systems. Production scheduling manages the flow of materials or components through the manufacturing system [2].

According to Gershwin [3], production control policies may be categorized as token-based, time-based and surplus-based. Token-based systems involve kanban [4], production authorization card [5] and extended kanban control systems [6]. Nothing is produced unless one token exist for it. When an operation is performed or a demand arrives, a token is either created or taken from a specific location. Time-based systems operate on a time basis; for example, earliest due date (EDD) [7] and material requirements planning (MRP) systems [8] attempt to determine the time at which an operation should take place. 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 multiple machines systems to smooth the production flow and reduce the negative effects brought about by machine failures. If the upper buffer(s) is empty then the machine has no part to process (starvation). On the other hand if the downstream buffer(s) is full then the machine cannot produce any more part (blockage). Production networks are controlled based on WIP level and capacity of buffers, and their main objective is to avoid both starvation and blockage.

Partially completed components are called WIP inventory. The WIP level is highly related to the fluctuations of demand. WIP is accumulated when the actual production rate is higher than demand. In fact a trade off is needed in the number of WIP, for a manufacturing system. Some of the advantages of WIP are listed in the following [9]:

1. Putting a buffer and some amount of WIP between two machines will provide independence of their operations,
2. WIP allows second machine in a two machines series to work on the next part when the first machine is broken down,
3. WIP inventory allows two machines in series to work on different part types, even if there is a significant setup time required to change from one part type to another.

But the WIP level should stay as small as possible, because [10]:

1. Capital invested to inventories as long as they remain in the factory provides no profit,
2. High in-process inventories increase cycle times and decrease responsiveness to customers,
3. High in-process inventories require more space and expensive material handling equipment.
4. Inventory quality decreases as the unfinished items remain in the factory would be exposed to damage.

In this paper genetic fuzzy logic controlling (GFLC) system [2 and 11] is developed for multi-part-type production line. The genetic algorithm (GA) [12] is implemented to optimize the performance of WIP fuzzy controllers. The main objective of scheduling problem 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) for the fuzzy controller. The overall methodology is to model the manufacturing system using simulation software (Simulink®), designing the fuzzy controllers and developing GA for tuning their membership functions. Running the simulated model of manufacturing system is needed even in practical experiments. After evolving the fuzzy controllers, one can implement them in real controlling systems. Beside of evaluating the performance of the proposed controlling system; this paper provides basic model for multi-part-type production lines. Figure 1 shows the main framework of this methodology. The detailed methodology will be explained in sections 3, 4 and 5.

The rest of the paper is organized as follows. Section 2 reviews some of previous literatures. Then heuristic fuzzy control structures (which are introduced in [9 and 13]) are described in Section 3. Section 4 describes the implementation of GA in fuzzy controllers. Section 5 presents the development of the controlling system for a multi-part-type production line. The modeling and simulation results of this controlling system are presented in section 6. Finally the conclusion and some suggestions for further development are presented in Section 7.

![Fig. 1. Main framework of GFLCs](image)

2 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) [9]. Sharifiia [14] discussed about a surplus-based production control system of a single-product manufacturing system with arbitrary number of machine states. He found a production policy that meet 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.

Another approach was presented by Bai and Gershwin [15 and 16]. Their method is based on the determination of a desirable production surplus value, 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 [15 and 16] 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 [17]. Custodio et al. [18] addressed planning and scheduling problems using an approach supported by fuzzy theory. The methodology uses a hierarchical structure, which includes three decision levels (higher, middle, and lower). The higher decision level determines safety stock levels used to compensate for future resource failures. At the middle level, loading rates are computed. Finally, the lower level controls the row of parts among the resources, using fuzzy decision method.

Tedford and Lowe [19] proposed an order release mechanism incorporating an adaptable fuzzy logic system 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. Song and Sun [20] studied a single part manufacturing 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.

Tsourveloudis et al. [9] considers single and multiple part type production lines and networks with finite buffers and unreliable machines. The objective is to keep the WIP and cycle time at low levels. They developed a fuzzy logic controller (FLC) for each machine and the output of this controlling system is the production rate of machine. Ioannidis et al. [13] proposed a supervisory controller to tune a set of lower level distributed fuzzy controllers. Tsourveloudis et al. [2 and 11] developed a genetic algorithm for the optimization of generic WIP scheduling fuzzy controllers. The GA was used to tune a set of fuzzy control modules which are used for distributed and supervisory WIP scheduling. The GA identified the MFs for which the fuzzy controller performs optimally with respect to WIP and backlog minimization.
3 Heuristic Fuzzy Controller

3.1 Heuristic Distributed Fuzzy (HDF) Controllers

Tsourveloudis et al. [9] proposed a fuzzy structure for controlling WIP level in a manufacturing system. This methodology was called distributed fuzzy control, because the controlling modules are distributed in production processes and control each machine separately. The aims of this controlling module are to minimize the WIP while satisfying demand and avoiding blockage or starvation. These controllers control production rate for each machine. As it is illustrated in figure 2, each controlling module is connected to its preceding (B_j) and following (B_i) controlling stations, through joint-controlled upstream and downstream buffers.

![Fig. 2. Distributed fuzzy controller [9]](image)

In distributed fuzzy controlling 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 controlling module is the production rate for machine i. The core of controlling system is the FLC. There are two main rules for controlling the machines:

1. If there is no sign of machine starving or blockage, then keep the production surplus close to zero.
2. 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:

**IF** \( b_{ij} \) is \( LB^{(k)} \) AND \( b_{ij} \) is \( LB^{(k)} \) AND \( ms \) is \( LMS^{(k)} \) AND \( x_i \) is \( LX^{(k)} \) **THEN** \( r_i \) is \( LR^{(k)} \).

The \( k \) is the rule number (\( k = 1; \ldots ; 18 \)), \( i \) is the number of machines or workstations, \( LB \) is a linguistic value of the variable buffer level \( b \) with term set \( B = \{Empty; Almost Empty; OK; Almost Full; Full\} \); \( ms \) 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 \( R = \{zero; Low; Normal; High\} \).

It is obvious that if the machine is off then the production rate is zero. Finally all the active rules are aggregated simultaneously, and through a centroid formula the final crisp value for production rate is calculated:

\[
\hat{r}_i = \frac{\sum r_i \mu_i^*(r_i)}{\sum \mu_i^*(r_i)}
\]

where \( \mu_i^*(r_i) \) is the MFs of the aggregated production rate.

3.2 Heuristic Supervisory Fuzzy (HSF) Controllers

Ioannidis et al. [13] developed a heuristic supervisory fuzzy controller to tune HDF controlling modules. The overall production control system was viewed as a two level surplus-based system. 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 \( x_e \) and the initial lower bound of surplus \( l_e \).
3. The relative WIP error \( ew \) which is:

\[
ew = \frac{\text{WIP}(t) - \text{WIP}(t)}{\text{WIP}(t)}
\]

where \( \text{WIP}(t) \) is the mean WIP (including 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, \( \text{WIP}(t) \) is used as a target value.

![Fig. 3. Supervisory fuzzy control architecture [13]](image)

The supervisory controller output variables are the production surplus upper and lower bound correction factors \( (u_e \) and \( l_e \)), where \(-1 \leq l_e, u_e \leq 1\). 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 \( u_0 \), 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:

\[
\begin{align*}
    u_b &= l_b + u_n + \min(x_e, 0) \\
    l_b &= \min([l_j + i_n], u_b)
\end{align*}
\]  

(3)

where \( l_i \) and \( l_j \) are the initial upper and lower surplus bounds respectively, \( u_n \), \( n_l \) are constants chosen in such a way that \( l_b \) will never exceed \( u_0 \) when \( x_e \) is positive. The rule base of the supervisory controller contains rules of the following form:

IF \( mx \) is \( LMX^{(k)} \) AND \( e_x \) is \( LE_{e_x}^{(k)} \) AND \( e_w \) is \( LE_{e_w}^{(k)} \) THEN \( u_i \) is \( LU_u^{(k)} \) AND \( l_i \) is \( LL_i^{(k)} \)

where, \( k \) is the rule number \((k=1, \ldots, 29)\), \( LMX \) is a linguistic value of the variable mean end product surplus with term set \( MX = \{Negative Big, Negative Small, Zero, Positive Small, Positive Big\} \), \( e_x \) denotes the error of end product surplus which is the difference between surplus \( x \) and the lower bound \( l \), the term set of the corresponding linguistic value is \( EX = \{Negative, Zero, Positive\} \). \( LE_{e_w}^{(k)} \) 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 \( U_u \) from the term set \( U_u = \{Negative, Negative Zero, Zero, Positive Zero, Positive\} \) and the lower surplus bound correction factor takes linguistic values \( L_i \) from the term set \( L_i = \{Negative, Negative Zero, Zero, Positive Zero, Positive\} \).

4 Genetic Fuzzy Logic Controller

Fuzzy logic controllers use the knowledge of process (defined in form of fuzzy linguistic control rules), collected in a knowledge base (KB), to control the process. Most of the conventional methods in designing KBs were focused on obtaining the expert experiences from the human operators. The problem is occurred when there is no previous knowledge exists or the operators are not able to express their knowledge in terms of fuzzy variables [21]. GAs are introduced as powerful tools for automating the definition of KB [22].

The most interesting kind of genetic fuzzy systems is GFLCs. In GFLCs one can consider to optimize different components of KB. In this paper optimization of MFs of fuzzy controllers are considered. The efficiency of FLCs 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 FLC systems (distributed or sequential), a set of possible MFs are considered as the search space and initial population.

Tsourveloudis et al. [2 and 11] proposed the application of GAs for the optimal selection of MFs. As it is shown in figure 4, a chromosome is constructed by using the initial definition of MFs for all of the input variables [23]. MFs are selected to be in trapezoidal shape which has four critical parameters (a, b, c, d). 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. In each generation, a series of new chromosomes is created by crossover and mutation operators. These chromosomes are ranked based on their fitness (in this case the fitness function is performance of controlling system). A pre-determined number of best chromosomes are retained for being parents of next generation. The parents and new children (offspring) formed new population. The generation is continued for a pre-selected number or reaching a pre-determined performance number.

![Fig. 4. Chromosome created by the GAs.](image)

Based on Tsourveloudis et al. [2] these characteristics are chosen for the GA optimization of HSF:

1. The population number is 40.
2. The mutation rate is selected 0.1.
3. The 20 fittest individuals are qualified for the next generation.
4. Each individual is evaluated by the results of a simulation run of 200 time units.

5 Multi-Part-Type Production Controlling System

A complex production system can produce more than one part type by each machine. Bai and Gershwin [15] 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 is regulating 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 genetic supervisory fuzzy (GSF) controlling system [2] is shown in figure 5.

HDF controllers are used for the lower level controlling. The fitness function (which should be minimized) for GSF controllers is:

$$ F = C_w WIP + C_b BL $$

(4)

where, $WIP$ is the mean of work-in-process and $BL$ is the mean of backlog. $C_w$ and $C_b$ represent the unit costs of inventory and backlog, respectively. The vital importance of $WIP$ and $BL$ is shown in this controlling system, by using their unit costs in the fitness function.

![Fig. 5. Multi-part-type production system and GSF controlling structure for it.](image)

6 Modeling & Simulation Results

GSF controllers are implemented for multi-part-type production system. Based on the structure of the GSF controlling 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 supervisory controller and the second box is the production system box. In addition, there is a box for GA optimizer. Figure 6 illustrates the content of production control system box. The production system box is containing machine subsystems, WIP statistics boxes, surplus and backlog statistics boxes and cycle time statistics boxes. HDF controllers are used inside each machine block to determine the production rate of each machine (this is not shown in figure 6).

The GA optimization which is described in section 4 is not a complicated system. The controlling system is quite similar to the HSF and HDF controlling systems. This controlling system needs as many distributed fuzzy controllers as the number of virtual machines exist and as many supervisory controllers as the number of part types (in this test case there are eight HDF controllers and two GSF controllers). To optimize this controlling system one may run a simulation to achieve the best MFs for the supervisory system. After gaining the optimized definition of MFs for HSF controlling modules, the system can work properly in real environments. The Matlab® fuzzy logic tool box [24] and GA tool box [25] are used to construct the controlling system and Simulink® [26] is used to simulate the production system.

The proposed GSF approach is tested and compared with the heuristic approaches introduced in [13]. 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 assumption (same to assumption of [13]) 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.
3. Demand is constant and known with rate $d_i$
4. The processing time for each part type at each machine is 0.325. Each machine produces in a rate $r_i \leq \mu_i$, where $\mu_i$ 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 buffer levels at any time instant are given by:
$$b_{j,(k+1)} = b_{j,(k)} + (r_j - r_i)$$
where $r_j$ is the rate of production for upstream machine and $r_i$ is rate of production for downstream machine.

The performance of the GSF controlling 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](image)

Figure 8 illustrates the WIP level for various demands and various rates of failure. Both of these graphs show that GSF controlling systems generally have better performance than HSF controlling systems. 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 controlling systems, for various WIP & 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](image)

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>
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<tr>
<th>Demand</th>
<th>$C_t$</th>
<th>$C_b$</th>
<th>HSF WIP BL</th>
<th>C</th>
<th>GSF WIP BL</th>
<th>C</th>
</tr>
</thead>
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<tr>
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<td>0.25</td>
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<td>3.67</td>
<td>1.12</td>
<td>3.03</td>
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</table>

7 Conclusion

A new test case for the GSF system 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 multi-part-type production system 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 controlling 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.

8 References


