On the Evolutionary-Fuzzy Control of WIP in Manufacturing Systems

Nikos C. Tsourveloudis

Department of Production Engineering and Management
Technical University of Crete
73100 Chania, Crete, Greece
nikost@dpem.tuc.gr

Abstract. The effectiveness of optimized fuzzy controllers in the production scheduling has been demonstrated in the past through the extensive use of Evolutionary Algorithms (EA) for the Work-In-Process (WIP) reduction. The EA strategy tunes a set of distributed fuzzy control modules whose objective is to control the production rate in a way that satisfies the demand for final products, while reducing WIP within the production system. The EA identifies optimal design solutions in a given search space. How robust and generic is the controller that comes out of this process? This paper faces this question by testing the evolutionary tuned fuzzy controllers in demand conditions other than the ones used for their optimization. The evolutionary-fuzzy controllers are also compared to heuristically designed ones. Extensive simulations of production lines and networks show that the evolutionary-fuzzy strategy achieved a substantial reduction of WIP compared to the heuristic approach in all test cases.

Keywords: Manufacturing Systems, Work-In-Process, Fuzzy Control, Evolutionary Algorithms, Controller Design.

1 Introduction

As the manufacturing industry moves away from the mass production paradigm towards the agile manufacturing, the life cycle of products gets shorter while the need for a wide variety of them increases. Keeping large inventories in stock tends to be unattractive in today's markets. The same holds for the unfinished parts throughout the manufacturing system, widely known as Work-In-Process (WIP), as it represents an already made expense with unknown profitability due to the rapidly changing demand. In a highly changing demand environment, the accumulated inventories are less desirable than ever.

The work-in-process inventory is measured by the number of unfinished parts in the buffers throughout the manufacturing system and it should stay as small as possible (for various reasons reported in [1], [2] and elsewhere).

Control policies aim in keeping WIP at low levels [3]. However, an exact optimal value of WIP cannot be determined in realistic manufacturing conditions. Therefore, the problem of WIP determination and control is amenable to an artificial intelligent treatment, as suggested in [4], [5] and recently in [6], [8].

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Fuzzy logic has been used in tandem to Evolutionary Algorithms (EA) so as to keep the WIP and cycle time as low as possible and at the same time to maintain high utilization [7], [9]. The objective in those works was to optimize the control policy in a way that satisfies the (random) 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 has an optimal performance with respect to WIP minimization for several demand patterns.

The use of evolving genetic structures for the production scheduling problem, has recently gained a lot of acceptance in the automated and optimal design of fuzzy logic systems [10], [11]. However, a potential problem is that the evolutionary (or genetically) evolved fuzzy controllers might perform optimal only under the conditions involved in the evolution process. In this paper we examine the performance of evolutionary optimized controllers in contrast to heuristically designed fuzzy controllers. For comparisons purposes we test the controllers in conditions different from the ones they have been designed for. In this way, some useful insights regarding the design robustness of the evolutionary tuned fuzzy controllers may be drawn.

The rest of the paper is organized as follows. Section 2 describes the evolutionary fuzzy scheduling concept that is used for WIP minimization. Section 3 describes the comparison scenarios and presents experimental results for production lines and networks. Issues for discussion and remarks as well as suggestions for further development are presented in the last section.

2 Evolutionary-Fuzzy Scheduling

Traditionally, a production system is viewed as a network of machines and buffers. Items are received at each machine and wait for the next operation in a buffer with finite capacity. WIP may increase because of unanticipated events, like machine breakdowns and potential consequent propagation of these events. For example, a failed machine with operational neighbors forces to an inventory increase of the previous storage buffer. If the repair time is big enough, then the broken machine will either block the previous station or starve the next one. This “bottleneck” 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. The expert knowledge that describes the control objective (that is WIP reduction) can be summarized in the following statements [5], [8]:

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

else

If the surplus is not satisfactory that is either too low or too high then produce at maximum or zero rate respectively.

In fuzzy logic controllers (FLCs), the control policy is described by linguistic IF-THEN rules similar to the above statements. The essential part of every fuzzy controller is the knowledge acquisition and the representation of the extracted knowledge with certain fuzzy sets/membership functions. Membership functions (MFs) represent the uncertainty modeled with fuzzy sets by establishing a connection between linguistic terms (such as low, negative, high etc) and precise numerical values of variables in the physical system. The correct choice of the MFs is by no means trivial but plays a crucial role in the success of an application. If the selection of the membership functions is not based on a systematic optimization procedure then the adopted fuzzy control strategy cannot guarantee minimum WIP level [9].

The evolutionary-fuzzy synergy attempts to minimize the empirical/expert design and create MFs that fit best to scheduling objectives [7], [9]. 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. Evolutionary Algorithms (EAs) are seeking optimal or near optimal solutions in large and complex search spaces and therefore have been successfully applied to a variety of scheduling problems with broad applicability to manufacturing systems [10]. 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 are retained for the next generation. Then parents are selected repeatedly from the current generation of chromosomes, and new chromosomes are generated from these 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. The architecture of evolutionary-fuzzy WIP control scheme is presented in Fig. 1 and it is extensively discussed in [7] and [9].

The performance measure (fitness function) used in all previous treatments considers a known demand for products and the cumulative production of the system that produces these products. A typical fitness $F(x_i)$, of each individual x_i is:

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

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.

Assuming that the capacity of a production system is given, equation (1) shows that the evolved MFs are highly based (in terms of their support and shape) on the demand values. Some questions arise here: What if the actual demand is different (in both magnitude and changing pattern) than the one assumed in the evolution of the fuzzy controller? Is the evolved controller robust enough to absorb variations in demand? Or the original (without MF optimization) heuristic fuzzy performs better in unknown demands? Since there are no analytical solutions to those questions, in what follows we will examine and compare the performance of both evolutionary and heuristic fuzzy controllers through simulation, for a wide variety of test cases.

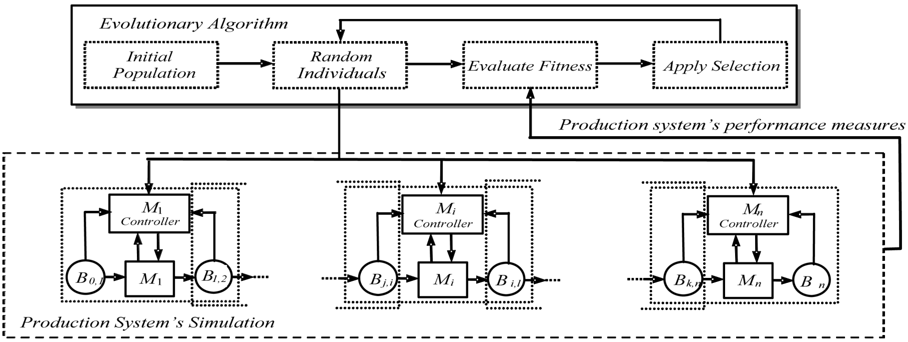

Fig. 1. Evolutionary-fuzzy control concept

3 Testing and Results

The evolutionary-fuzzy approaches suggested in [7], are tested and compared to the heuristic fuzzy approaches initially suggested in [5]. In the all simulations performed we assume that the machines fail randomly with a failure rate p_i. This rate is known and set before the simulation starts. Also, machines are repaired randomly with rate rr_i. The resources needed for repairs are assumed to be unlimited. The times between failures and repairs are exponentially distributed. All machines operate at known, but not necessarily equal rates. Each machine produces in a rate $r_i \le \mu_i$, where μ_i is the maximum processing rate of machine M_i. We also assume that the flow of parts within the system is continuous.

The initial buffers are infinite sources of raw material and consequently the initial machines are never starved. The buffer levels at any time instant are given by:

$$b_{j,i}(t_{k+1}) = b_{j,i}(t_k) + [r_j(t_k) - r_i(t_k)](t_{k+1} - t_k), \tag{2}$$

where t_k, t_{k+1}, r_i are the times when control actions (changes in processing rates) happen. The cumulative production of a machine M_i is

$$PR_i(t_{k+1}) = PR_i(t_k) + r_i(t_k)(t_{k+1} - t_k). \tag{3}$$

In all simulations runs set-up and transportation times are negligible or included in the processing times. Buffers between adjacent machines M_i, M_j assumed to have finite capacities.

Two common layouts of a production system are considered. A production line (Fig. 2a) and a production network (Fig. 2b). In Figure 2, circles represent buffers and the squares are machines. For simplicity both systems are assumed to produce one part type. Lines and networks producing multiple part types have been discussed in [5], [6] and it has been shown that have similar behavior to the single-part-type systems. The production systems of figure 2 are identical to the systems discussed

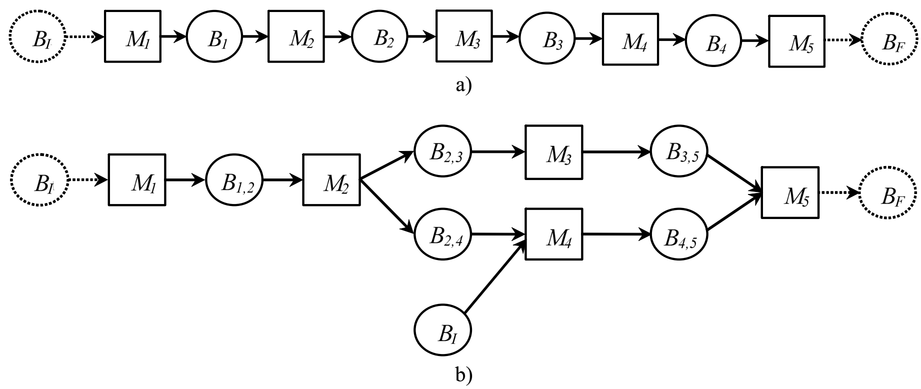

Fig. 2. The production systems used for controllers testing: a) Line, b) Network

in [5], [6], [7], [9]. This was selected on purpose so as to facilitate the comparisons with previous approaches. The main observation made in [6], [7] and [9] was that the evolutionary tuned fuzzy controllers achieved a substantial reduction of WIP in almost all test cases. This is expected since the controllers were evolved for known patterns of demand that is either constant or stochastic with certain mean values. In the test cases that follow, we keep unaltered the controllers' design but we scientifically change the demand patterns. In practice, and of course depending on the product, demand is the main uncertainty that comes from the outside of the production system.

3.1 Test Case 1: Production Lines

The production line under consideration (Fig. 2a) 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 $\mu_i = 2$ (i=1,...,5). All buffer capacities are equal to $BC_i = 10$.

In the evolution of the original fuzzy controllers for production lines, the demand was either considered constant (specified items per time unit) or stochastic (with known mean values and a small variation). Now the demand patterns are significantly changed, as can be observed in Figure 3. The value of $\overline{WIP}$ for both evolutionary (EFC: Evolutionary Fuzzy Controller) and heuristic (HFC: Heuristic Fuzzy Controller) is presented also in Figure 3. As can be seen the demand is far from being constant. For testing purposes, the demand shown in Figure 3 takes a random value between zero and 2.5 items every 20 time units. It has been observed that both controllers satisfy the demand and the same time achieve low WIP levels. But the evolutionary tuned is better than the heuristic one in the long run. This was the case in various tests with multiple changes in demand. As shown in Figure 4, for a more frequently changing demand, the evolutionary tuned controller is better in keeping WIP low than the heuristically designed controller.

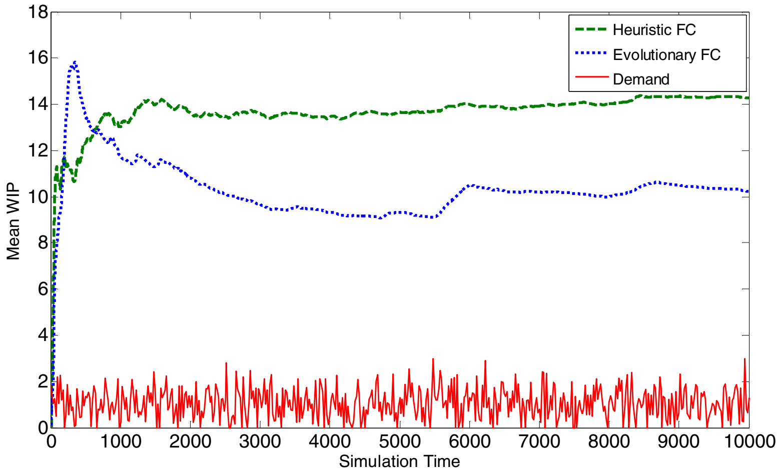

Fig. 3. Evolution of $\overline{WIP}$ in test case 1: Demand changes every 20 time units

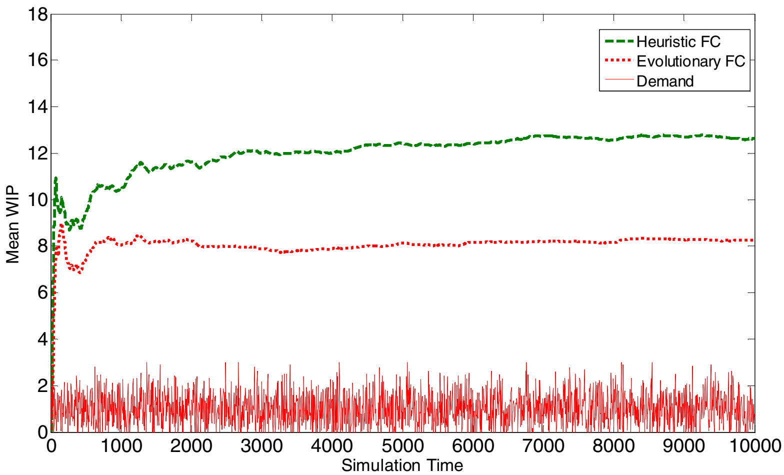

Fig. 4. Evolution of $\overline{WIP}$ in test case 1: Demand changes every 5 time units

3.2 Test Case 2: Production Networks

The production network (Fig. 2b) consists of five machines also 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 $\mu_i = 5$ (i=1,..., 5). All buffer capacities are equal to $BC_i = 10$.

As expected (and may be seen in Fig. 5), the $\overline{WIP}$ levels in test case 2 (production network) are higher than in the test cases 1 (production line). Also in test case 2 the

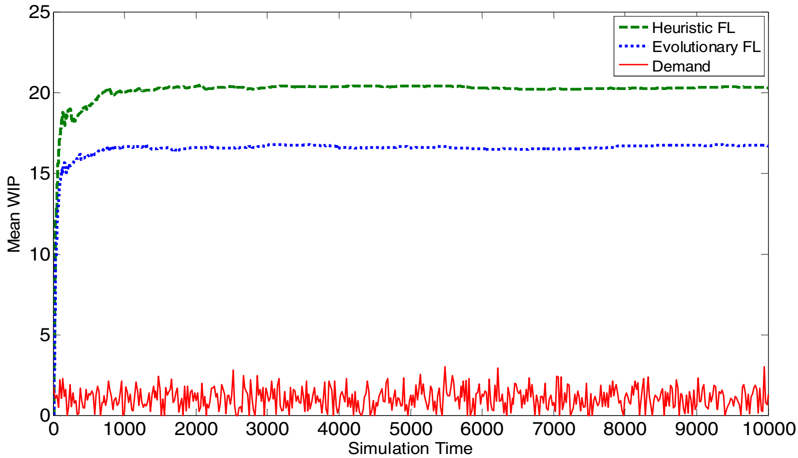

Fig. 5. Evolution of $\overline{WIP}$ in test case 2: Demand changes every 20 time units

evolutionary fuzzy controller gave less WIP than the heuristic fuzzy controller regardless of the demand changing frequency.

4 Observations and Concluding Remarks

A remarkable control ability of the WIP is shown in cases with a frequent demand change. This ability was observed regardless of production system's design complexity, as in both lines and networks the WIP is substantially reduced compared to the empirical selected fuzzy controllers.

It is known that WIP itself cannot represent adequately of production system's performance. One has to take into account also the accumulated orders backlog. It is also known that when demand is very high one may consider that service rate and thus backlog is more important than WIP. When demand can be easily satisfied and backlog is in low levels, a substantial reduction of WIP may be more important than a small increase in backlog. What we have seen so far is that with the aid of the evolutionary-fuzzy controllers the system's performance becomes more balanced in terms of mean WIP and backlog.

The heuristic fuzzy control approach cannot achieve the performance of the evolutionary-fuzzy. However, it is still better than previously reported "bang-bang" control approaches. Even when compared to the evolutionary-fuzzy approach it is much simpler in the design process as it steps on the human expertise/knowledge regarding the production system. In others words, one should very fast design, built and put to work a fuzzy controller with membership functions that represent the expert knowledge in contrast to the evolutionary-fuzzy system whose parameters are automatically set by the optimization procedure.

The evolutionary-fuzzy controllers are capable of maintaining low WIP levels for product demands other than the ones used during the optimization. Therefore, the evolutionary algorithms clearly represent a successful approach towards the optimization of robust scheduling approaches.

An interesting future extension of this work might be the use of EA strategies in more complex production systems such as multiple-part-type and/or reentrant systems.

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