ON THE WORK-IN-PROCESS CONTROL OF PRODUCTION NETWORKS

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Abstract: The effectiveness of evolutionary optimized fuzzy controllers for production scheduling has been proven in the past. The objective of the control/scheduling task in this context, is to continuously adjust the production rate in a way that: 1) satisfies the demand for final products, 2) keeps the inventory as low as possible. The evolutionary optimization identifies fuzzy control solutions which simultaneously satisfy those restrictions. The important question here is: How robust and generic is the outcome of the evolutionary process? In this paper we face this question by testing the evolutionary tuned fuzzy controllers under several demand patterns, as the actual demand might be different from those used for evolution\optimization. Extensive simulations of a supervisory controller identify the performance of the evolutionary-fuzzy strategy in comparison to a pure knowledge based one.

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 (Conway et al., 1998), (Bai and Gershwin, 1994).

Traditionally, inventory control methods in this field can be roughly grouped into mathematical modelling approaches, computerized planning methods, such as material requirement planning (MRP), and heuristic scheduling strategies. Many control policies (CONWIP-constant WIP, base stock method etc.|) aim in keeping WIP at low levels (Gershwin, 1994). 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 (Custodio et al., 1994), (Tsourveloudis et al., 2000) and recently in (Ioannidis et al., 2004) and (Tsourveloudis et al., 2006). The supervisory controller suggested in (Ioannidis et al., 2004) is used to tune a set of lower-level distributed fuzzy control modules that reduce WIP and synchronize the production system's operation. The overall control objective is to keep the WIP and cycle time as low as possible, while maintaining quality of service by keeping the backlog to an acceptable level.

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 (Tsourveloudis et al. 2006, Tsourveloudis et al., 2007). 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 (Tedford and Lowe, 2003, Gordon et al. 2001). However, a potential

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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. Two control approaches are presented: the *distributed* and the *supervised* one. 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

A production network consists of machines (operation stations) and buffers (storage areas). 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 neighbours 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 (Tsourveloudis et al, 2000, Tsourveloudis et al., 2006):

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 modelled 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 and 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.

The evolutionary-fuzzy synergy attempts to minimize the empirical/expert design and create MFs that fit best to scheduling objectives (Tsourveloudis et al., 2006). 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 (Tedford and Lowe, 2003). 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.

2.1 Distributed Evolutionary-fuzzy Control

The architecture of the distributed evolutionary-fuzzy WIP control scheme is extensively discussed in (Tsourveloudis et al., 2006) and (Tsourveloudis et al., 2007). The control objective of the distributed scheduling approach, as earlier stated, is to satisfy the demand and, at the same time, to keep WIP as low as possible. This is attempted by regulating the processing rate r_i at every time instant. The processing rate r_i of each machine at every time instant is:

$$r_i' = \mathrm{f}_{\mathrm{IS}}(b_{j,i}, b_{i,l}, x_i, s_i) = \begin{cases} 0 & \text{if } s_i = 0 \\ \dfrac{\sum r_i \mu_R^*(r_i)}{\sum \mu_R^*(r_i)} & \text{if } s_i = 1 \end{cases}, \quad (1)$$

where, $\mathrm{f}_{\mathrm{IS}}(b_{j,i}, b_{i,l}, x_i, s_i)$ represents a fuzzy inference system 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).

The fitness function $F(x_i)$ of each individual x_i, which associates the demand with the cumulative production of the manufacturing system is:

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

where, t is the current simulation time, $D(t)$ is the overall demand and $PR(t)$ is the cumulative production of the system.

As earlier stated, the objective of the evolution process is to optimize the shape of the fuzzy membership function. Indeed, after the evolution process the shape of the membership functions is altered. The best individual is considered to be the one with the biggest fitness. The fittest individuals are selected and they 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.

2.2 Supervised Evolutionary-fuzzy Control

In control systems literature a supervisor is a controller (supervisory controller) that utilizes available data to characterize the overall system's current behavior, potentially modifying the lower level controllers to ultimately achieve desired specifications. The supervisory controller in this, and also in our past works, is used to tune the distributed controllers in a way that improves performance without dramatic changes in the structure of the control architecture, as justified in (Ioannidis et al., 2004). The concept of the supervised evolutionary-fuzzy WIP control scheme is shown in Figure 1. The fitness function in the supervisory approach case was chosen to be the following:

$$F = \left(c_I \overline{WIP} + c_b \overline{BL} \right)^{-1} \quad (3)$$

where, $\overline{WIP}$ and $\overline{BL}$ are the mean work-in-process and mean backlog (=cumulative production minus demand), respectively. The c_I, c_b are weighting factors that represent the unit costs of inventory and backlog, respectively. Assuming that the capacity of a production system is given, equations (2) and (3) show that the evolved MFs are highly based (in terms of their support and shape) on the demand values. Obviously, the value of demand is crucial for WIP and backlog determination in (3). Some of the questions arise here concerning demand, are:

- What happens when actual demand is different (in both magnitude and changing pattern) than the one considered during controller's evolution?
- Is the evolved controller robust enough to absorb random variations of demand?
- Does the original (without MF optimization) heuristic fuzzy controller perform 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 variety of test cases.

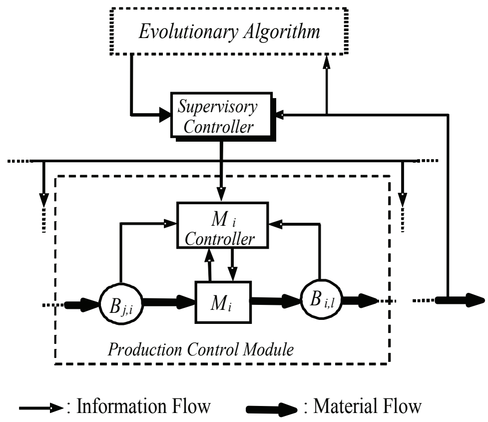

Figure 1: Supervisory control: Evolutionary-fuzzy concept.

3 TESTING AND RESULTS

The evolutionary-fuzzy approaches suggested in (Tsourveloudis et al., 2007), are tested and compared to the heuristic fuzzy approaches initially suggested in (Tsourveloudis et al., 2000). 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 available. 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 $r_i \leq \mu_i$, 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.

In the production network shown in Figure 2, the circles represent buffers and squares are machining stations. This network is identical to the one discussed in previous works (Tsourveloudis et al., 2000, 2006a, 2006b, 2007). For simplicity it is assumed that this network produces one part type. Lines and networks producing multiple part types have been discussed in (Tsourveloudis et al., 2000), (Ioannidis et al., 2004) and it has been shown that have similar behavior to the single-part-type systems. One important observation made in (Ioannidis et al. 2004, Tsourveloudis et al. 2006, 2007) was that the evolutionary tuned fuzzy controllers achieved a substantial reduction of WIP in almost all test cases.

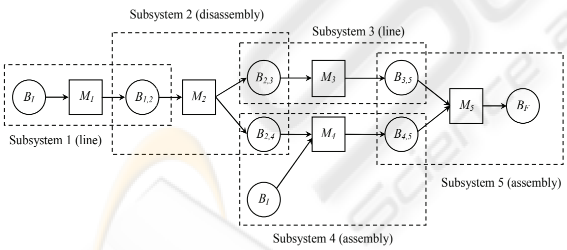

Figure 2: Layout of the production network.

Here we further investigate the performance of the evolutionary tuned fuzzy controllers, keeping unaltered the controllers' design but with demand patterns that are significantly changed. In practice, demand is the main uncertainty of almost all production system/networks. Changes in demand may cause significant problems in balancing production lines

3.1 Supervised Control of Networks

The objective is to examine the robustness of the supervised control approach. The simulation testbed used for this test case was developed in SIMULINK and its main blocks are shown in Figure 3.

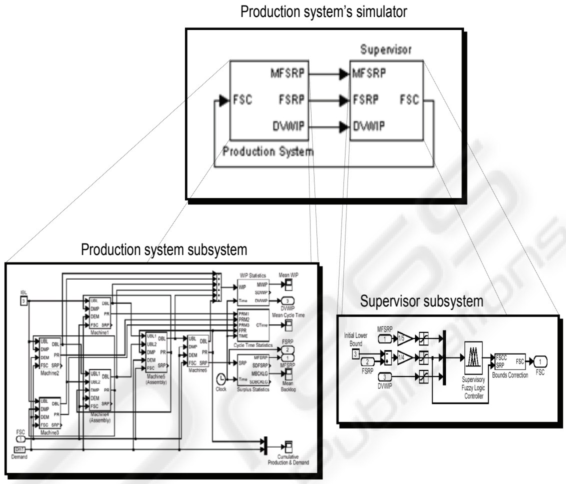

Figure 3: SIMULINK model of the supervisory control.

The performance of the evolutionary-fuzzy supervised approach was examined for various demand patterns other than the one used during the optimization of the membership functions. During the evolution procedure, demand was considered either one (one product per time unit) or zero (no demand at the time unit) and the selection between those two values was triggered in a random order. During our testing different demands were used:

Demand Pattern 1 (DP1): The system accepts orders of 1 product per time unit. The time unit is set equal to 0.05 of the simulation step. This is similar to the demand pattern used for the optimization of the controller.

Demand Pattern 1.5 (DP1.5): The system accepts orders for 1.5 products per time unit, which is set 0.05 of the simulation step.

Demand Pattern 3 (DP3): The system accepts orders for 3 products per time unit, which is also set 0.05 of the simulation step.

Figure 4 presents the mean WIP and Backlog for the above mentioned demand patterns. As it can be seeing, the mean WIP of DP1 is higher than the other two demands, but it fully satisfies the requested demand. DP1.5 and DP3 fail in satisfying demand in the same test run. It also can be seen, in Figure 4, that when the demand is 3 times higher (DP3) than the one used for the evolution (DP1), then it cannot be satisfied as the backlog accumulates rapidly (DP3-BL).

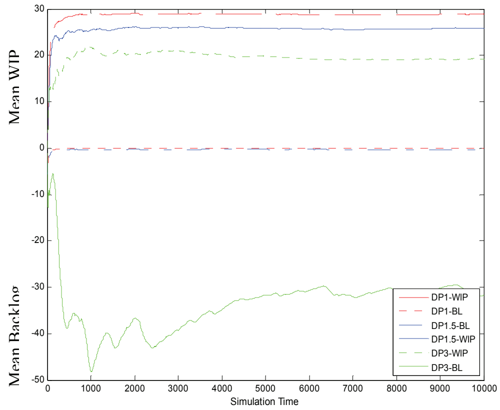

Figure 4: WIP and Backlog levels of the supervisory control for various demand sizes.

However, when demand is increased for 50%, (DP1.5) the unsatisfied demand (DP1.5-BL) is almost zero which shows that the supervisor works satisfactorily for demand changes of this magnitude: +50% of the demand used during the evolution of the fuzzy supervisory controller. This important observation was also noted through a series of simulation runs for demands lower than the one used in the evolution. In this case, a slight increase in the mean WIP levels was observed.

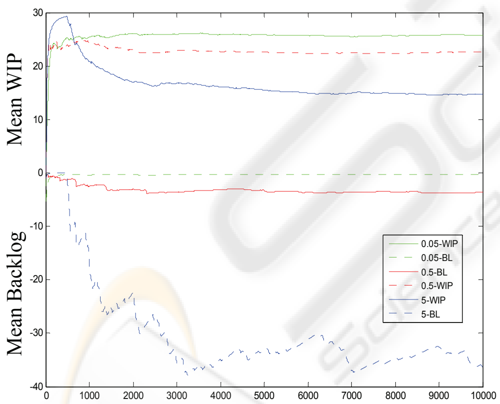

Figure 5: WIP and Backlog levels for changing demand rates.

Not only the magnitude but also the frequency of demand changing was examined. Figure 5 presents the WIP and Backlog mean levels when the DP1.5 demand pattern changes every 0.05, 0.5, and 5 time units respectively. It can be observed that in lower demand rates the controller keeps the backlog orders close to zero, while in higher rates although the controller keeps WIP in low levels, fails in satisfying the demand (5-BL in Figure 5).

4 CONCLUSIONS

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. WIP is substantially reduced in the evolutionary-fuzzy approach compared to the empirical selected fuzzy controllers. The same observation holds for the supervisory control of production networks where significantly increased demands were accommodated.

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.

REFERENCES

Conway R., Maxwell W, McClain J.O., Joseph Thomas L, 1998. The role of work-in-process inventory control: single-part-systems. Oper. Res. 36, pp. 229-241.

Bai S.X. and Gershwin S.B., 1994. Scheduling manufacturing systems with work-in-process inventory control: multiple-part-type systems. Int. J. Prod. Res. 32, 365-386.

Gershwin S.B ., 1994. *Manufacturing Systems*

Engineering. Prentice Hall, New Jersey.
Custodio L., Sentieiro J., Bispo C., 1994. Production planning and scheduling using a fuzzy decision system. IEEE Trans. Robot. Automat. 10, pp. 160-168.
Tsourveloudis N.C., Dretoulakis E., Ioannidis S., 2000. Fuzzy work-in-process inventory control of unreliable manufacturing systems. Inf. Sci. 27, pp. 69-83.
Ioannidis S., Tsourveloudis N.C., Valavanis K.P., 2004. Fuzzy Supervisory Control of Manufacturing Systems. IEEE Trans. Robot. Automat. 20, pp. 379-389.
Tsourveloudis N. C., L. Doitsidis, S. Ioannidis, 2006. Work-in-Process Scheduling by Evolutionary Tuned Distributed Fuzzy Controllers. In: Proceedings of the IEEE International Conference on Robotics and Automation, Orlando, FL, USA.
Tsourveloudis N. C., S. Ioannidis, K. P. Valavanis, 2006. Fuzzy Surplus based Distributed Control of Manufacturing Systems. Advances in Production Engineering and Management. 1, pp. 5-12.
Tsourveloudis N. C, Doitsidis L., Ioannidis S., 2007. Work-In-Process Scheduling by Evolutionary Tuned Fuzzy Controllers. International Journal of Advanced Manufacturing Technology. 34, no. 7-8, pp. 85-97.
Tedford J.D. and Lowe C., 2003. Production scheduling using adaptable fuzzy logic with genetic algorithms. Int. J. Prod. Res. 41, pp. 2681–2697.
Gordon O., Herrera F., Hoffmann F., Luis M., 2001. *Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Base.* World Scientific Publishing Co. Pte. Ltd, U.K.