Application of Artificial Intelligent in Production Scheduling: a critical evaluation and comparison of key approaches

Taravatsadat Nehzati
Department of Mechanical and Manufacturing Engineering, Faculty of Engineering, University Putra Malaysia, 43400 UPM, Serdang, Malaysia.

Napsiah Ismail
Department of Mechanical and Manufacturing Engineering, Faculty of Engineering, University Putra Malaysia, 43400 UPM, Serdang, Malaysia.

Abstract

Production scheduling is a part of operational research which relies on combinational optimization solved by discrete methods. This wide area covers different variety of problems like; vehicle routing problem, bin packing problem and job priority. In order to solve these problems, operational research applies two main principles: exact methods which provide the absolute best solution but solve only small sized problems, and approximate methods which provide only good solution but solve near real life sized problem. The second category provides various methods divided into: problem dedicated methods called heuristics and general method called metaheuristics. Many of these metaheuristic methods are leading the literature of production scheduling for past two decade, like; Genetic Algorithm, Neural Network, and Fuzzy Logic which will be discuss in this paper. This review shows that there are only few research works which compare heuristic techniques on scheduling problem. There is a need for scholars to focus on evolutionary manufacturing systems, and hybrid models to face scheduling problem.

Keywords
Production Scheduling, Artificial Intelligence, Metaheuristic Model, Genetic Algorithm, Fuzzy Logic

1. Introduction
Sequencing and scheduling is a form of decision-making that plays a crucial role in manufacturing and service industries. In the current competitive environment effective sequencing and scheduling has become a necessity for survival in the marketplace. Companies have to meet shipping dates who have been committed to customers, as failure to do so may result in significant loss of goodwill. They also have to schedule activities in such a way as to use the resources available in an efficient manner.
The main issues associated with scheduling of FMSs are machine loading, part routing, tool planning and allocation, material handling device assignment, and routing as well as task timing problems [34]. It is a decision making process with the goal of optimizing one or more objectives. The resources and tasks in an organization can take many forms. The task can be operated in a production process. Each task may have a certain priority level, an earliest possible starting time, and a due date. The objectives also can take many forms. One objective may be the minimization of completion time of the last task, [34] and another may be the minimization of the number of tasks completed after their respective due dates. [30]

1.1 Production Scheduling Trend in Manufacturing
Scheduling began to be taken seriously in manufacturing at the beginning of 20th century, with the work of Henry Gantt and other pioneers. However, it took many years for the first scheduling publications to appear in industrial engineering and operation research literature. Some of the first publication appeared in Naval Research Logistics Quarterly in the early 1950s and contained results by S.M Johnson and J.R Jackson. During the 1960s a significant amount of works was done by dynamic programming and integer programming formulations of scheduling problems. After Richard Karp's famous paper on complexity theory, the research in the 1970's focused mainly on

the complexity hierarchy of scheduling problems. In the 1980s several different directions were pursued in academia and industry with the increase amount of attention paid to stochastic scheduling problems. Also, as personal computers started to permeate manufacturing facilities, scheduling systems were being developed for the generation of usable schedule in practice. This system design and development was, and is, being done by computer scientists, operations researchers and industrial engineers.

By the end of 1970's and early in 80s researchers started using Artificial Intelligent (AI) as a means to cope with uncertainty reasoning in production scheduling [4]. Within these years considerable amount of effort has been directed towards the representation and manipulation of uncertain information. For last two decades the issue of uncertainty is an important consideration during any decision-making process and scheduling is no exception [19, 30]. Within the scheduling domain there is a large degree of uncertainty both from environmental uncertainties (machine breakdown or rush orders) and scheduling uncertainties (repercussions of which are exponential and thus too costly to evaluate) which considered by recent researchers [1, 6 and 30].

In this paper brief investigation has been done on recent literatures in production scheduling by employing Artificial Intelligence (AI) as a response to scheduling uncertainties (see Figure 1). Three main AI techniques among recent literature have been spread in following sections. Therefore, section 2 presents the application of fuzzy technique, while section 3 presents application of neural network in production scheduling problem whereas section 4 deals with genetic algorithm in this issue. Finally, a certain probe developed for hybrid artificial intelligence in section 5.

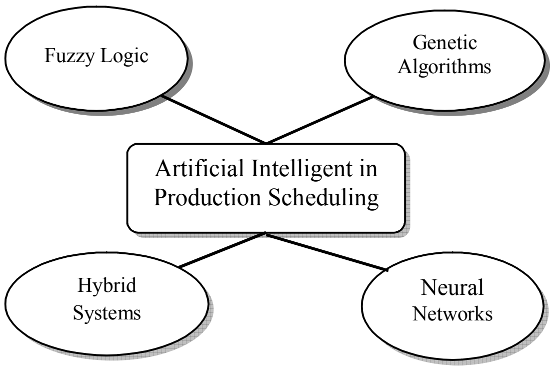

Figure 1 components of an Intelligent Production Scheduling

2. Fuzzy Logic System

Fuzzy set theory was introduced in 1965 by Zadeh [32,33]. Fuzzy sets and their extension to dealing with linguistic variables [33] were later successfully employed in many engineering applications. Fuzzy sets are also particularly useful in control problems, due to the development of fuzzy logic systems (FLS), widely described in the literature (e.g., [19, 21]). Using fuzzy logic to control flexible manufacturing systems seems very appropriate due to its lenience in coping with uncertain data, in company with the multi-objective nature of the problem. Hintz and Zimmermann [14] are probably the first to propose a production planning and control system that uses fuzzy set theory. The interesting part of their work consists in the application of approximate reasoning techniques to both the sequencing and the priority setting problems. The authors develop a hierarchy of elements that are important to make a decision in both cases. This methodology is quite general, thus it can be easily modified and extended by changing the backgrounds. The consequent of the rules are the next job to be entered into the system (sequencing) or to be processed (priority setting).

The performance of this fuzzy controller is compared to common heuristics by means of discrete event simulations of a particular FMS configuration [14]. As a result, fuzzy expert systems seem to perform better then heuristics in terms of mean waiting time, number of in-time (i.e., not late) parts and mean machine utilization. This approach is very innovative for introducing a fuzzy expert approach to scheduling, but it also suffers from being an early approach, in that it only considers sequencing and priority setting. Moreover, the scheduling rules are predetermined with human expert aid and no explicit design procedure is presented. The multiple objective nature of the problem is also not thoroughly investigated, because the comparison with heuristic approaches is done on a limited number of production objectives.

Choobineh and Shivani [5] approach the priority setting and routing problems using fuzzy set theory along with possibility theory. Fuzzy sets are used to model the uncertainty of data and the vagueness involved with human planning. For every possible routing of a part, an aggregate possibility distribution is determined according to the possibility distributions of single attributes of a resource. These possibility distributions are combined into one aggregate possibility distribution, by means of a weighted average, with weights being (trapezoidal) fuzzy numbers expressing the importance of the given attribute (i.e., indifferent, not important, somehow important, important, very important). In this study no comparisons with standard heuristics are presented, moreover the multiple objective nature of the problem is not accounted for, since Work In Process (WIP), due dates, utilization and tardiness are not explicitly considered.

Watanabe et al. [29] propose a fuzzy scheduling mechanism for job shops, that they name FUZZY. The only problem that they actually attack is the priority setting problem for a free machine choosing in its buffer the next job to serve. The authors consider clients demands and divide the orders into three categories: normal, express and just in time (JIT). The proposed fuzzy scheduler employs non-singleton fuzzifier, max-min inference and center of gravity defuzzifier. All the membership functions are triangular. The fuzzy scheduler was then tested through computer simulations and compared to common priority setting heuristics, i.e., SPT, LS and HPFS. In all the benchmark tests FUZZY produced the highest profit, but only average tardiness performance. Watanabe's work is limited to one particular aspect of scheduling and does not consider some important objectives like WIP, throughput and utilization. The proposed fuzzy technique is very limited in that it only uses two rules and two fuzzy sets for each antecedent.

Angsana and Passino [2] seem to be the first to have a more systematic approach to the problem. They present a fuzzy controller for the priority setting problem along with a procedure that can be used for both design and adaptation. This constitutes the real novelty of their work, even though at a very preliminary stage. The authors at first consider the problem of a single machine and build a fuzzy controller (FC) for it. Considering an FMS where every machine has such a controller a distributed fuzzy controller (DFC) is obtained. It is assumed that each machine has a different buffer for every part type. By using the buffer levels they implement a fuzzy version of the clear largest buffer (CLB) heuristic policy. This policy tries to empty the fullest buffer giving priority to the parts it contains. The authors conclude that it is not always better to use a large number of fuzzy sets.

Tavakoli-Moghadam et al. [27] attempt to minimize the total weighted tardiness and makespan simultaneously. In single machine scheduling problem, a proposed fuzzy multi-objective linear programming (FMOLP) method is applied with respect to the overall acceptable degree of the decision maker (DM) satisfaction.

Considering the complexity of scheduling problem [25] various researches demonstrated that fuzzy logic would be efficient technique to solve production scheduling, as an NP hard problem.

3. Artificial Neural Networks

Artificial neural networks (ANNs) are currently widely used in several engineering applications. These connectionist structures try to mimic the human brain with a distributed neural-synaptic-cognitive structure. Artificial neural networks have greatly matured since the early perception and associative memories. In some way they can be regarded as a "overly parameterized" nonlinear function whose weights can be determined by optimizing some measure of performance of the network (generally its "distance" by a set of given test points). For more detailed readings on ANNs, Kosko [19] and Haykin [13] are suggested. ANNs offer advantages like the possibility of learning, the existence of several structures for the attaining of particular objectives, high speed (in the utilization phase) and eventual hardware implementation. On the other hand they might be slow to train and the set of "weights" (parameters) that they finally have do not have a real physical meaning to the user. These, along with the fact that fuzzy systems can be regarded as adaptive networks and thus trained with the same paradigms used for neural networks, make fuzzy logic systems a more suitable means for engineering applications. Anyway, some interesting applications of ANN to the scheduling problem exist in the literature and they are briefly reviewed in the following.

Lo and Bavarian [20] use a Hopfield neural network to predictively solve the assignment problem of parts to resources. This neural network is extended to a three dimensional structure called neuro box network (NBN) where the three axes correspond to time, machine and part. The authors minimize an energy function corresponding to the time needed to execute the schedule with the addition of some terms corresponding to the feasibility of the given schedule. Thus, their approach consists in using a Hopfield neural network to solve a constrained minimization problem having as an objective function the length of the schedule. The results are presented in term of convergence of the method but no comparison with common heuristics is given. Moreover, only one production objective is considered and the approach is predictive. While generally real-time approaches are preferred, in this case an important factor is the learning speed of the network.

Hao et al. [11] propose a three phase decisional structure for the routing problem as well as the selection of the transportation unit (i.e., AGV) to use. The first phase is a filtering stage where among all the routing possibilities the unfeasible ones (e.g., routing to a failed machine) are excluded. One neural network with one hidden layer is used and no mention is given to its training, besides a "right" choice of weights. In the second phase the results of the first phase are used to determine the best one among all the feasible alternatives. An optimizing modified Hopfield-Tank neural network is used. The stable output of this network corresponds to the routing most appropriate for the current system state. Finally, the third phase determines the proper sequence of actions needed to follow the selected route. A self-organizing Kohonen network is used. This network has the advantage of being initialized with a single node and to automatically evolve through processes of addition and deletion of nodes. Hao et al. [11] do not present any comparison result or testing of the approach, even though the implementation on a given FMS configuration is discussed. Within its own limitation this work is interesting because of the consideration of the phase division of the problem. Indeed such a structure is open to modification of one or more of its phases, keeping the others the same.

4. Genetic Algorithms

Genetic algorithms are an optimization technique that is efficient for complex and high-dimension problems with *irregular* objective functions where generally gradient-based techniques fail. They were introduced by Holland 15in 1975 and later developed by Goldberg [10] among others. These algorithms conduct a random search starting from an initial population that iteratively *evolves* by means of certain operators. This *evolution* corresponds to moving towards areas in the search space corresponding to the maximum of a given objective function that represent the *fitness* of a particular individual (solution). Because of their characteristics GAs seem to be particularly suited for scheduling problem, as also remarked by Tsang in a comparative study of scheduling approaches [28]. Given their nature, GAs are used for predictive scheduling, that is, to determine an optimal schedule at the beginning of a fixed time horizon. This is probably the limit in the use of GAs for scheduling purposes. With the increasing computational power available at decreasing costs GAs might become particularly suited for a predictive scheduling that approaches reactive scheduling. Indeed by decreasing their targeted time horizon they could be used in a predictive fashion on very small time steps, thus approximating a real-time approach. The very key of this evolution of the role of GAs stands in the objective function evaluation time. If very small (compared to the time horizon) evaluation times can be achieved then a quasi real-time solution can be found. Constraint representation and expression is another problem with GAs, even though some solutions exist. In the following some examples of use of GAs in scheduling are listed very briefly to show some of the existing approaches.

Gen et al. [6], Kim and Lee [17] and Asadzadeh and Zamanifar [3] use a GA to determine a schedule for a job-shop. The objective function is the schedule length. Falkenauer and Bouffouix [8] use a GA to determine a schedule for a job-shop where the objective is lateness minimization and earliness maximization. Sittisathanchai et al. [26] present a GA for job-shop scheduling. The objective is the minimization of the schedule length along with its cost. The cost of the schedule is defined in terms of lateness and operations advance. Dorndorf and Pesch [6] use a GA as a training source for some standard heuristics. A job-shop scheduling problem is considered, where the objective is the minimization of the schedule length. Holsapple et al. [16] use a GA to present random examples to a predictive AI based FMS scheduler. The scheduler learns autonomously from these examples.

5. Hybrid systems

Malakooti et al [21] developed a monitoring and supervising system for machining operations using in-process regression for monitoring and adaptive feed forward artificial NNs for supervising. The monitoring system predicts tool life by using different sensors for gathering information based on regression model that allows for the variations between tools and different machine setups [22]. The regression model makes its prediction by using the history of other tools and combining it with the information obtained about the tool under consideration. Ming et al. [23] has combined expert systems and NNs to develop a CAPP system. Other attempts have been made to use AI in managing dependent demand inventories. A wider discussion can be found in the review of [24]. Table 1 is summarizing the reviewed techniques.

Table 1 : Artificial Intelligent techniques in production scheduling

		Reference
Technique	Fuzzy Logic	Angsana and Passino [2]Choobineh and Shivani [5] Hintz and Zimmermann [14] Kosko [19] Tavakoli-Moghadam et al. [27] Runkler et al.[25]
	Genetic Algorithms	Asadzadeh and Zamanifar [3]Dorndorf and Pesch [6] Gen et al [9] Goldberg [10] Holland [15] Holsapple et al[16] Sittisathanchai et al[26] Tsang,[27] Falkenauer and Bouffouix [8]
	Neural Networks	Hao et.al [11] Haykin [13] Kosko [19] Lo and Bavarian [20]
	Hybrid Systems	Malakooti et al [21] Ming et al [23] Proudlove et al [24] Maziane et al [22]

6. Conclusions

In this paper a review of fuzzy techniques for scheduling in flexible manufacturing system was made. Elements of neural, AI based and GA based techniques were presented too. Every fuzzy approach, besides the one presented by Angsana and Passino [2], lacks of a systematic design procedure that could hold for different FMS configurations. On the contrary, all neural network based techniques have a design procedure that basically consists in the training of the network. This type of training has drawbacks in terms of speed and data collection. Deciding how to evaluate the reward for a given action is basic in implementing any of these techniques and can be a quite complex task. This constitutes one of the main obstacles in developing design and adaptation solutions. Every fuzzy approach, besides the one of Hatono et al. [12], implement rules either based on some fuzzy version of existing heuristics or based on expert knowledge. This way already working and tested solutions can be embodied in the fuzzy framework and optimized. Both neural and AI-hybrid based approaches are based on some production objectives, generally only one of them. This is easily explained given the type of neural network training or inductive learning.

Not all the reviewed techniques were tested and compared to heuristic or already existing solutions. Moreover if they were, they were only compared in terms of a limited number of production objectives. This picture of the state of the art in intelligent techniques for scheduling in FMS shows the definite need for a systematic design procedure based on multiple objectives. Moreover the design procedure should also account for the stochastic and dynamic nature of the system. Some general modifiable structure for designing according to multiple production objectives with different degrees of importance is absent. Such a framework could be the first step towards a truly adaptive solution to the scheduling problem. On these premises the use of fuzzy logic seems very suitable. Indeed fuzzy multiple attribute decision making techniques could offer the advantage of being able to deal with multiple and contrasting objectives. Fuzzy logic systems could be used to deal with uncertain and vague data and to code expert's knowledge. Fuzzy techniques can also take advantage of rules, as expert systems, and deal with vagueness. Looking at fuzzy systems as some kind of bridge between neural and AI based solutions it can be concluded that a fuzzy hybrid solution should be sought.

7. Future Research Direction

A current trend in manufacturing plants is to move towards highly flexible production systems that can respond quickly to demand changes and to the processing of a variety of products. In light of this fact new paradigm of Reconfigurable Manufacturing System (RMS) introduced [18]. By growth of this new concept, further work should be planning to put RMS aspects into consideration and adopt different techniques in reconfigurable environments.

References

1. Adonyi, R., Biros, G., Holczinger, T., and Friedler, F., 2008,"Effective scheduling of large-scale paint production system," Journal of Cleaner Production, 16, 225-232.
2. Angsana, A., and Passino, K.M., 1993,"Distributed intelligent control of flexible manufacturing systems," Proceeding of the 1993 American Control Conference, 1520-1524.
3. Asadzadeh, L., and Zamanifar, K., "An agent-based parallel approach for the job shop scheduling problem with genetic algorithms," Mathematical and Computer Modeling. (in press)
4. Berry, P.M., 1993, "Chapter 3: Scheduling and Uncertainty Reasoning," appears in Scheduling of Production Processes, Dorn, J., Froeschl, K.A., (eds.), Ellis Horwood Publication, 31-47.

5. Choobineh, F., and Shivani, M., 1992, "Dynamic process planning and scheduling algorithm," Proceedings of the Japan/USA Symposium on Flexible Automation, ASME, 429-432.
6. Choy, K.L., Leung, Y.K., Chow, H.K.H., Poon, T.C., Kwong, C.K., Ho, G.T.S., and Kwok, S.K. "A hybrid scheduling decision support model for minimizing job tardiness in a make-to-order based mould manufacturing environment," Expert Systems with Applications. (in press)
7. Dorndorf, U, .and Pesch, E., 1995, "Evolution based learning in a job-shop scheduling environment," Computers and Operations Research, 22(1), 25-40.
8. Falkenauer, E., and Bouffouix, S., 1991, "A genetic algorithm for job-shop," Proceedings of the IEEE International Conference on Robotics and Automation, 1, 824-829.
9. Gen, M., Tsujimura, Y., and Kubota, E., 1994, "Solving job-shop scheduling problems by genetic algorithms," Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, 2, 1577-1582.
10. Goldberg, D.E., 1989, Genetic Algorithms in search, optimization and machine learning, Addison-Wesley.
11. Hao, G., Shang, J.S., and Vargas, L.G., 1994, "A Neural network approach for the real time control of a FMS," Proceedings of the Hawaii International Conference on System Sciences, 3, 641-648.
12. Hatono, I., Suzuka, T., Umano, M., and Tamura, H., 1992, "Towards intelligent scheduling for flexible manufacturing: application of fuzzy inference to realizing high variety of objectives," Proceedings of the Japan/USA Symposium on Flexible Automation, ASME , 1, 433-440,.
13. Haykin, S., 1994, Neural Networks, Macmillan/IEEE Press.
14. Hintz, G.W. and Zimmermann, H.J., 1989, "A method to control flexible manufacturing systems," European Journal of Operational Research, 41 (3), 321-334.
15. Holland, J., 1975, Adaptation in Natural and Artificial Systems, The University of Michigan Press.
16. Holsapple C.W., Jacob, V.S., Pakath, R., and Zaveri, J.S., "A Genetics-based hybrid scheduler for generating static schedules in flexible manufacturing contexts," IEEE Transactions on Systems Man and Cybernetics, vol. 23, n. 4, July-August 1993, 953-972.
17. Kim, G.H. and Lee, C.S.G., 1994, "An evolutionary approach to the job-shop scheduling problem," Proceedings of the IEEE International Conference on Robotics and Automation, 1, 501-506.
18. Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., and Ulsoy, G., (1999), "Reconfigurable manufacturing systems". CIRP Annals - Manufacturing Technology*,* 48(2), 527-540.
19. Kosko, B., 1992, Neural Networks and Fuzzy Systems - a dynamical system approach to machine intelligence, Prentice Hall.
20. Lo, Z.P. and Bavarian, B., April 1991, "Scheduling with neural networks for flexible manufacturing systems," Proceedings of the IEEE International Conference on Robotics and Automation, 818-823.
21. Malakooti, B.B., Zhou, Y.Q., and Tandler, E.C., 1995, "In-process regression and adaptive multicriteria neural networks for monitoring and supervising mechaning operation," Journal of Intelligent Manufacturing, 6 (1), 53-66.
22. Maziane, F., Vadera, S., Kobbacy, K., and Nathan, P., 2000, "Intelligent systems in manufacturing: current developments and future prospect," Journal of Intelligent Manufacturing System, 11 (4), 218-238.
23. Ming, X.G., Mak, K.L. and Yan, J.Q. 1999,"A hybrid intelligent inference model for computer aided process planning," The International Journal of Manufacturing Technology Management, 10(6), 343-53.
24. Proudlove, N.C., Vaders, S., and kobbacy, K.A.H., 1998, "Intelligent management systems in Operations: a review", Journal of the Operational Research Society, 49(7), 682-99.
25. Runkler, T.A., Sollacher, R., and Revery, W., 2004, "Distributed Fuzzy Decision making for production scheduling," mathware and Soft Computing, 11, 211-244.
26. Sittisathanchai, S., Dagli, C.H., and Lee, H.C., 1994, "A genetic scheduler for job shops," Proceedings of the Artificial Neural Networks in Engineering Conference, 351-356.
27. Tavakoli-Moghadam, R., Javadi, B., Jolai, F., and Ghodratnama, A., 2010, "The use of multi-objective linear programming for solving a multi-objective single-machine scheduling problem," Applied Soft Computing, 10(3), 919–925.
28. Tsang, E.P.K, January 1995, "Scheduling techniques - a comparative study," BT Technology Journal, 13(1), 16-28.
29. Watanabe, T., Tokumaru, H,. and Hashimoto, Y., 1993,"Job-Shop scheduling using neural networks," Control engineering practice, 1(6), 957- 961.
30. Wu, D., and Ierapetritou, M., 2007, "Hierarchical approach for production planning and scheduling under uncertainty," Chemical Engineering and Processing, 46(11), 1129–1140.
31. Yalaoui, N., Dugardin, F., Yalaoui, F., Amondeo, L., and Mahdi, H., 2010, "Chapter 8: Fuzzy Project Scheduling," appears in Production Engineering and Management under Fuzziness, Kahraman, C., Yauz, R. (eds.), Springer Berlin, Heidelberg, 143 – 170.
32. Zadeh, L.A., 1965, "Fuzzy sets," Information and Control, 8, 338-353.
33. Zadeh, L.A., January 1973, "Outline of a new approach to the analysis of complex systems and decision processes," IEEE Transactions on Systems, Man and Cybernetics, 3(1), 28-44.
34. Zeballos, L.J., "A constraint programming approach to tool allocation and production scheduling in flexible manufacturing systems," Robotic and Computer-Integrated Manufacturing*,* (in press).