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CHRONOLOGICAL EVOLUTION OF FLEXIBLE JOB SHOP SCHEDULING: A REVIEW

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Abstract*- Job shop scheduling is the technique to provide appropriate solutions for single or multi objective manufacturing processes. In recent years, researchers have provided solutions for scheduling jobs through utilizing dispatching rules, genetic algorithms (GA) and fuzzy priority rules. This research reviews the chronological development of techniques in solving the job shop scheduling from dispatching rules to fuzzy priority rules which are classified in three steps namely dispatching rules, genetic algorithms (GA) and fuzzy job shop scheduling. Also, suggestions are made regarding in future further improvement techniques to solve the job shop scheduling problems more efficiently.*

Keywords: Scheduling, Job Shop, Dispatching Rule, Genetic Algorithm, Fuzzy Priority Rule.

1. INTRODUCTION

Scheduling is the process of arranging, controlling and optimizing work and workloads in a production process or manufacturing process. Scheduling is used to allocate plant and machinery resources, plan human resources, plan production processes and purchase materials. Multi-stage scheduling problems consist of a set of n jobs requiring execution on more than one machine. Each of these jobs has a set of operations needing to be processed on a set of machines. Each job visits the machines following a certain order known as the processing route. If the processing routes are not given in advance, and have to be chosen, the scheduling problem is called an open shop configuration [1]. If each job has a fixed and exclusive processing route, the problem is called job shop configuration. In this configuration, the processing route of operations is determined in advance but is not identical for all the operations [2]. If the processing routes are fixed and are identical for all the jobs, the problem is called a flow shop [3]. Job shop scheduling is an optimization problem in computer science and operations research in which ideal jobs are assigned to resources at particular times. This problem is a class of combinational optimization problems known as non-deterministic polynomial-hard (NP-Hard) problems [4]. Job shop Scheduling is one of the most significant issues in production planning. If there are n, jobs J_1, J_2, ..., J_n of varying sizes, which need to be scheduled on m identical machines, while trying to minimize the makespan. The makespan is the total length of the schedule (that is, when all the jobs have finished processing). Nowadays, the problem is presented as an online problem (dynamic scheduling), that is, each job is presented, and the online algorithm needs to make a decision about that job before the next job is presented. From 1960s to 2000, researchers have mainly focused on dispatching rules for solving the job shop scheduling problems. Around 2000 researchers started to use genetic algorithms (GA) to find solutions for job shop scheduling. Although the fuzzy technique was first used to solve the job shop scheduling problems in 1995. Recently researchers are shifting the focus to use the fuzzy rules or make a combination between genetic algorithms (GA) and fuzzy rules. But still it is considered that the research on job shop scheduling in its infancy stage. Present paper aims to gather and review the availability literature published throughout the last two decades.

2. IMPORTANCE OF SCHEDULING

Within an organization scheduling refers to establishing the timing of the use of specific resources of that organization. It relates to the use of equipment, facilities and human activities. Scheduling occurs in every organization regardless the nature of its activities. Schedule derives its importance from two different considerations:

(i). In sufficient scheduling results in poor utilization of available resources. An obvious symptom here is the idleness of facilities, human resources and equipment waiting for orders to be processed. As a results production costs increase and this reduces the competiveness or effectiveness of the organizations.

(ii). Poor scheduling frequently creates in the flow of orders through the systems. This calls for more expenditure that again increase costs, upset previous plans and delay some orders whose late delivery results in unhappy customers. Effective scheduling can yield cost savings and increase productivity. The other benefits of production scheduling include are process change-over reduction, inventory reduction, leveling, reduced scheduling effort, increased production efficiency, labor load leveling, accurate delivery date quotes, real time information etc. Thus in competitive environments effective scheduling can give a competitive advantage in terms of customer scheduling.

3. LITERATURE REVIEW

A large number of approaches to the modeling and solution of the job shop scheduling problems have been used, with varying degrees of success. These approaches revolve around a series of technological advances that have occurred over that last 35 years. These include mathematical programming, dispatching rules, expert systems, neural networks, genetic algorithms, and inductive learning. In this paper, it takes an evolutionary view in describing how these technologies have been applied to job shop scheduling problems. To do this, we review a few of the most important contributions in each of these technology areas and the most recent trends.

3.1 Mathematical Techniques

Mathematical programming has been applied extensively to job shop scheduling problems. Problems have been formulated using integer programming, mixed-integer programming and dynamic programming. Until recently, the use of these approaches has been limited because scheduling problems belong to the class of NP-complete problems. To overcome these deficiencies, a group of researchers began to decompose the scheduling problem into a number of sub problems, proposing a number of techniques to solve them [12]. In addition, new solution techniques, more powerful heuristics, and the computational power of modern computers have enabled these approaches to be used on larger problems.

3.2 Decomposition Strategies

Davis et al. (1988) proposed a methodology based on the decomposition of mathematical programming problems that used both Benders-type and Dantzig/Wolfe-type decompositions. The methodology was part of closed-loop, real-time, two-level hierarchical shop floor control system. The top-level scheduler (i.e., the supremal) specified the earliest start time and the latest finish time for each job. The lower level scheduling modules (i.e., the infimals) would refine these limit times for each job by detailed sequencing of all operations. A multi criteria objective function was specified that included tardiness, throughput, and process utilization costs. In general, N sub problems would result plus a constraint set that contained partial members of each of the sub problems [12]. The supremal unit explicitly considered the coupling constraints, while the infimal units considered their individual decoupled constraint sets. The authors pointed out that the inherent stochastic nature of job shops and the presence of multiple, objectives made it difficult to express the coupling constraints using exact mathematical relationships.

3.3 Recent Trends

Model-Based Optimization (MBO) is an optimization approach that uses mathematical expressions (e.g., constraints and inequalities) to model scheduling problems as mixed integer (non) linear programs (MINLP's). A set of methods such as linear programming, branch-and-bound, and decomposition techniques are used to search the scenario space of solutions. Due to the advances in computer technologies, the computation times are becoming very practical. According to Subrahmanyam et al. (1996) For problems of moderate size, solutions of type D are given. Solutions of type D, are optimal solutions of the maximum desirability possible within the constraints of operation. These approaches are being enhanced by the development of English-like "scheduling languages" and high-level graphical interfaces [12]. The scheduling languages support the developing of the mathematical formulations with minimum intervention from the user.

3.4 Dispatching Rules

Dispatching rules have been applied consistently to scheduling problems. They are procedures designed to provide good solutions to complex problems in real-time. The term dispatching rule, scheduling rule, sequencing rule, or heuristic are often used synonymously. Dispatching rules have been classified mainly according to the performance criteria for which they have been developed. Wu (1987) categorized dispatching rules into several classes. Class 1 contains simple priority rules, which are based on information related to the jobs. Sub-classes are based on the particular piece of information used. Example classes include those based on processing times (such as shortest processing time (SPT)), due dates (such as earliest due date (EDD)), slack (such as minimum slack (MINSLACK)), and arrival times (such as first-in first out (FIFO)). Class 2 consists of combinations of rules from class one. The particular rule that is implemented can now depend on the situation that exists on the shop floor [12]. A typical example of a rule in this class is, for example, SPT until the queue length exceeds 5, then switch to FIFO. During the last 30 years, the performance of a large number of these rules has been studied extensively using simulation techniques (Montazer et al.1990).

3.5 Artificial intelligence (AI) techniques

Starting in the early 80s, a series of new technologies were applied to job shop scheduling problems. They fall under the general title of artificial intelligence (AI) techniques and include expert systems, knowledge-based systems, and several search techniques. Expert and knowledge-based systems were quite prevalent in the early and mid, 1980s. They have four main advantages. First, and perhaps most important, they use both quantitative and qualitative knowledge in the decision-making process. Second, they are capable of generating heuristics that are significantly more complex than the simple dispatching rules described above. Third, the selection of the best heuristic can be based on information about the entire job shop including the current jobs, expected new jobs, and the current status of resources, material transporters, inventory, and personnel. Fourth, they capture complex relationships in elegant new data structures and contain special techniques for powerful manipulation of the information in these data structures there are, however, serious disadvantages. They can be time consuming to build and verify, as well as difficult to maintain and change [12].

3.6 Expert/knowledge-based systems

Expert and knowledge-based systems consist of two parts: a knowledge base, and inference engine to operate on that knowledge base. Formalizations of the “knowledge” that human experts use rules, procedures, heuristics, and other types of abstractions are captured in the knowledge base. Three types of knowledge are usually included: procedural, declarative, and meta. Procedural knowledge is domain-specific problem solving knowledge. Declarative knowledge provides the input data defining the problem domain. Meta knowledge is knowledge about how to use the procedural and declarative knowledge to actually solve the problem. Several data structures have been utilized to represent the knowledge in the knowledge base including semantic nets, frames, scripts, predicate calculus, and production rules. The inference engine selects a strategy to apply to the knowledge bases to solve the problem at hand. It can be forward chaining (data driven) or backward chaining (goal driven). ISIS (Fox 1983) was the first major expert system aimed specifically at job shop scheduling problems. ISIS used a constraint-directed reasoning approach with three constraint categories: organizational goals, physical limitations and causal restrictions. Organizational goals considered objective functions based on due-date and work-in progress [12]. Physical limitations referred to situations where a resource had limited processing capability.

3.7 Distributed AI: agents

The problem solving ability of a single expert or knowledge based system, these AI approaches have difficulty solving large scheduling problems as well. To address this, AI researchers have also begun to develop distributed scheduling system approaches (Parunak et al., 1985). They have done this by an application of their well-known "divide and conquer" approach. This requires a problem decomposition technique, such as those described above, and the development of different expert/knowledge-based systems that can cooperate to solve the overall problem (Zhang et al. 1995). The AI community's answer is the "agent" paradigm. An agent is a unique software process operating asynchronously with other agents. Agents are complete knowledge-based systems by themselves. The set of agents in a system may be heterogeneous with respect to long term knowledge, solution-evaluation criteria, or goals, as well as languages, algorithms, hardware requirements. Integrating agents selected from a library creates a multi-agent system [12]. For example, one such multi-agent system could involve two types of agents: tasks and resources. Each task agent might be responsible for scheduling a certain class of tasks such as material handling, machining, or inspection, on those resources capable of performing those tasks.

3.8 Artificial neural networks

Neural networks, also called connectionist or distributed parallel processing models, have been studied for many years in an attempt to mirror the learning and prediction abilities of human beings. Neural network models are distinguished by network topology, node characteristics, and training or learning rules. Through exposure to historical data, supervised learning neural networks attempt to capture the desired relationships between inputs and the outputs [12]. Back-propagation is the most popular and widely used supervised training procedure. Back-propagation (Rumelhart et al., 1986, Werbos 1995) applies the gradient-descent technique in the feed-forward network to change a collection of weights so that some cost function can be minimized.

3.9 Temporal reinforcement learning

It was noted above that supervised learning neural networks attempt to capture the desired relationships between inputs and the outputs through exposure to training patterns. However, for some problems, the desired response may not always be available during the time of learning. When, the desired response is obtained, changes to the neural network are performed by assessing penalties for the scheduling actions previously decided by the neural network. As summarized by Tesauro (1992), “In the simplest form of this paradigm, the learning system passively observes a temporal sequence of input states that eventually leads to a final reinforcement or reward signal (usually a scalar). Several procedures have been developed to train neural networks when the desired response is not available during the time of learning [12]. Rabelo et al., (1994) utilized a procedure developed by Watkins (1989), denominated Q-learning, to implement a scheduling system to solve dynamic job shop scheduling problems. The scheduling system was able to follow trends in the shop floor and select a dispatching rule that provided the maximum reward according to performance measures based on tardiness and flow time.

3.10 Tabu search

The basic idea of Tabu search is to explore the search space of all feasible scheduling solutions by a sequence of moves (Glover et al., 1989, 1990). A move from one schedule to another schedule is made by evaluating all candidates and choosing the best available, just like gradient-based techniques. Some moves are classified as tabu (i.e., they are forbidden) because they either trap the search at a local optimum, or they lead to cycling (repeating part of the search). These moves are put onto something called the Tabu List, which is built up from the history of moves used during the search. These tabu moves force exploration of the search space until the old solution area (e.g., local optimum) is left behind. Another key element is that of freeing the search by a short term memory function that provides “strategic forgetting”. Tabu search methods have been evolving to more advanced frameworks that includes longer term memory mechanisms. These advanced frameworks are sometimes referred as Adaptive Memory Programming (AMP, Glover 1996). Vaessens (Glover 1996) showed that tabu search methods (in specific job shop scheduling cases) are superior over other approaches such as simulated annealing, genetic algorithms, and neural networks [12].

3.11 Fuzzy logic

Fuzzy set theory has been utilized to develop hybrid scheduling approaches. Fuzzy set theory can be useful in modeling and solving job shop scheduling problems with uncertain processing times, constraints, and set-up times. These uncertainties can be represented by fuzzy numbers that are described by using the concept of an interval of confidence. These approaches usually are integrated with other methodologies (e.g., search procedures, constraint relaxation). For example, Slany (1994) stresses the imprecision of straight-forward methods presented in the mathematical approaches and introduces a method known as fuzzy constraint relaxation, which is integrated with a knowledge-based scheduling system. His system was applied to a steel manufacturing plant [12]. Grabot and Geneste (1994) use fuzzy logic principles to combine dispatching rules for multi-criteria problems. Tsujimura et al., (1993) presented a hybrid system, which uses fuzzy set theory to model the processing times of a flow shop scheduling facility. Triangular Fuzzy Numbers (TFNs) are used to represent these processing times. Each job is defined by two TFNs, a lower bound and an upper bound.

3.12 Reactive Scheduling

Reactive scheduling is generally defined as the ability to revise or repair a complete schedule that has been "overtaken" by events on the shop floor (Zweben et al., 1995). Such events include rush orders, excessive delays, and broken resources. There are two approaches: reactive repair and the proactive adjustment. In reactive repair, the scheduling system waits until an event has occurred before it attempts to recover from that event. The match-up techniques described in section 3 fall into this category [12]. Proactive adjustment requires a capability to monitor the system continuously, predict the future evolution of the system, do contingency planning for likely events, and generate new schedules, all during the execution time of the current schedule. The work of Approaches that are more recent utilize artificial intelligence and knowledge-based methodologies (Smith 1995). Still most of the AI approaches propose a quasi-deterministic view of the system, i.e., a stochastic system featuring implicit and/or explicit causal rules. The problem formulation used does not recognize the physical environment of the shop floor domain where interference not only leads to readjustment of schedules but also imposes physical actions to minimize them.

3.13 Theory of Constraints

The Theory of Constraints (TOC) developed by Eliyahu Goldratt (1990, 1992) is the underlying philosophy for synchronized manufacturing. Goldratt (1990) defined synchronized manufacturing as any systematic method that attempts to move material quickly and smoothly through the production process in concert with market demand. A core concept to TOC is the idea that a few critical constraints exist. Goldratt contends that there is only one constraint in a system at any given time. As defined by Dettmer (1997), a constraint is “any element of a system or its environment that limits the output of the system”. A constraint will prevent increases in throughput regardless of improvements made to the system. The best schedule is obtained by focusing on the planning and scheduling of these constraint operations [12]. In essence, the constraint operations become the basis from which the entire schedule is derived. TOC has several important concepts and principles. Among them (Goldratt 1990,1992):

(i). Systems function like chains.
(ii). The system optimum is not the sum of the local optima.
(iii). The effect-cause-effect method identifies constraints.
(iv). System constraints can be either physically or policy.
(v). Inertia is the worst enemy of a process of ongoing improvement.
(vi). Throughput is the rate at which the entire system generates money through sales.
(vii). Inventory is all the money the system invests in things it intends to sell.

4. DISCUSSION

Optimization is the process of finding the greatest or least value of a function for some constraint, which must be true regardless of the solution. In other words, optimization finds the most suitable value for a function within a given domain. For providing optimization solution for JSSP (job shop scheduling problem) the techniques utilized can be classified in five broad categories:

a. Dispatching rules.
b. Genetic algorithm.
c. Fuzzy rule.
d. Combination of fuzzy rule and genetic algorithm.

4.1 Dispatching rules

Dominic et al. (2004) did comparisons among FIFO, LIFO, LPT, MWKR, MWKR_FIFO, MWKR_SPT, SPT, TWKR, and TWKR_SPT through simulation in order to find most efficient dispatching rules for dynamic job shop scheduling. They found that the combined rules MWKR_FIFO and MWKR_SPT fared best in fulfilling the objective of minimizing performance measures. Vinod et al. (2010) experimented with different combination of due date assignment and scheduling rules in order to find best possible combination for each performance measure criterion. Mohanasundaram et al. proposed four new rules - ECT-FIFO and LF-ECT considering lead time based objectives and, JDD-FIFO and LFD-JDD based on due date objectives [9]. They compared the results with the finding of Adam et al. (1987) and Adam et al. (1993) who concluded that TWKR-RRP rule is best for minimizing flow time and staging delay and, JDD rule is best suited for minimizing mean tardiness. The comparison revealed that the

LF-ECT rule performed very well for lead time based measures, and for due date measures, LFD-JDD produced good results.

4.2 Genetic Algorithms

Niu et al. customized the IWD (Intelligent Water Drops) algorithm for solving multi-objective job shop scheduling and developed MOJSS-IWD algorithm which aims to find the best compromising solutions considering multiple criteria namely makespan, tardiness, mean flow time of schedule [11]. It was found that, in general that MOJSS-IWD algorithm can generate comparable results considering the previously mentioned three criteria. As a results MOJSS-IWD algorithm more robust solution for MOJSS.

4.2.1 Variable Neighborhood Search

Variable neighborhood search (VNS) with set up times had been used by Roshanaei et al. to minimize the makespan during processing of operations [1]. VNS, a recently proposed metaheuristic technique, has quickly gained widespread success. VNS algorithms have shown excellent capability to solve scheduling problems to optimal or near-optimal schedule. The term “variable neighborhood search" refers to all local search-based approaches that are centered on the principle of systematically exploring more than one type of neighborhood structure during the search. The reason for the utilization of VNS is that metaheuristics are stuck in local optima, the move required to improve the solution cannot be performed and the moves in the neighborhood would lead to a deterioration of the solution quality very high.

4.2.2 Four-dimensional Algorithm

Four-dimensional algorithm is a heuristic optimization algorithm for scheduling [5]. Its basis is the minimum evaluation index. The any element of the evaluation index has great probability to make total makespan minimization when other factors are fixed. It can be found that the time-consuming of the four dimensional algorithm is 40~60 times more than the general genetic algorithm and simulated annealing algorithm. The total optimization probability is 88.75%. Comparing with the genetic algorithm and the simulated annealing algorithm, the method can enhance effect of optimization 31%~34% for the 5000 operation scheduling problems where there are 100 jobs and 50 machines.

4.2.3 Robust scheduling with random machine breakdown

Robust scheduling for multi-objective flexible job-shop problems with random machine breakdowns used by Xiong et al. [6]. Two objectives makespan and robustness are simultaneously considered. Robustness is indicated by the expected value of the relative difference between the deterministic and actual makespan. Two surrogate measures for robustness are developed. Specifically, the first suggested surrogate measure considers the probability of machine breakdowns, while the second surrogate measure considers the location of float times and machine breakdowns. Most literatures regarding robust project scheduling are focused on resource- constrained project scheduling. Al-Fawzan et al. (2005) proposed a robustness measure of a given schedule that is based on the total amount of free slack for all activities. Kobylan et al. (2007) proved the deficiencies of the robustness measure in Al-Fawzan et al. (2005) and modified this measure to be the minimum of the ratios of free slack.

4.2.4 Scatter search with path relinking

Scatter search with path relinking for the flexible job shop scheduling problem it proposed effective neighborhood structures for this problem, including feasibility and non-improving conditions, as well as procedures for fast estimation of the neighbours quality. These neighborhoods are embedded into a scatter search algorithm which uses tabu search and path relinking in its core. Scatter Search (SS) is a population-based evolutionary metaheuristic recognized as an excellent method at achieving a proper balance between intensification and diversification in the search process.

4.2.5 Genetic Algorithm with Intelligent Agents

Local search genetic algorithm with intelligent used by L. Asadzadeh have been implemented successfully in many scheduling problems in particular job shop scheduling [8]. The framework of the local search genetic algorithm agents is carried out repeatedly until satisfying the generation span. Hybridization is an effective way of improving the performance and effectiveness of genetic algorithms. Local search techniques are the most common form of hybridization that can be used to enhance the performance of these algorithms. Agent-based systems technology has generated lots of excitement in recent years because of its promise as a new paradigm for conceptualizing, designing, and implementing software systems.

4.3 Fuzzy Rule

Canbolat et al. (2009) using fuzzy logic introduced a combination of SPT, CR priority rules, and next machine’s load (NML) and named this priority rule as fuzzy priority rule (FPR). To compare FPR with other priority rules such as SPT, EDD etc. we run simulation. The results indicate significant improvements on mean flow time, mean tardiness, work in process.

4.4 Fuzzy Rule with Genetic Algorithms

Liu et al. developed an improved EDA (Estimation of Distribution Analysis) by including the historical optimal solution & the standardized solution vector and named it fEDA (fast Estimation of Distribution Analysis) [10]. By applying the Taguchi method of design of experiments, they demonstrated that the fEDA outperforms the original EDA on the convergence speed and the precision of the results. Lei (2010) developed a random key genetic algorithm with a new decoding strategy incorporating maintenance operation.

5. LIMITATIONS IN OPTIMIZATION OF THE JSSP

The classification of JSSP in terms of chronological development of their applicability, ability to approximate real world solution and methodologies have been reviewed in study paper. Although JSSP very important subjects the literatures found in this subject is not sufficient and there is huge gap in combining the different JSSP techniques. In case of JSSP, no single rule performs best in all situations, even combination of two rules does not guarantee a solution appropriate for all situations. There is no absolute assurance that a genetic algorithm will find a global optimum. Like other intelligence techniques the genetic algorithm cannot assure constant optimization response time. It is unreasonable use genetic algorithms on line control in real systems without testing them first on a simulation model. For optimization in JSSP in case of fuzzy rule it often produces result which is close to optimum. So, finding exact optimum solution cannot be guaranty. It uses random selections and random techniques in their procedure for providing a solution for JSSP.

6. CONCLUSION

Nowadays, job shop scheduling plays an effective scheduling combination for any type of production and service floor using its various diversification. Although some specific area it has some limitations, but it helped to schedule effectively in complex region to bring out the most feasible and optimum solutions.

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8. NOMENCLATURE

Symbol	Meaning
NP	Non-deterministic Polynomial
GA	Genetic Algorithm
MBO	Model-Based Optimization
MINLP	Mixed Integer Non Linear Programming
SPT	Shortest Processing Time
EDD	Earliest Due Date
MINSLACK	Minimum Slack
FIFO	First in First Out
AI	Artificial Intelligence
AMP	Adaptive Memory Programming
TFN	Triangular Fuzzy Number
TOC	Theory of Constraint
LIFO	Last in First Out
LPT	Longest Processing Time
MWKR	Most Work Remaining
MWKR_FIFO	Most Work Remaining First in First Out
MWKR_SPT	Most Work Remaining Shortest Processing Time
JSSP	Job Shop Scheduling Problem
TWKR	Total Work Remaining
ECT_FIFO	Earliest Completion Time First in First Out
LF_ECT	Latest Finish Earliest Completion Time
JDD_FIFO	Job Due Date First in First Out
LFD_JDD	Latest Finish Date Job Due Date
RRP	Relative Remaining Operation
FFD_JDD	First Fit Decreasing Job Due Date
MOJSS-IWD	Multi Objective Job Shop Scheduling Intelligent Water Drop
VNS	Variable Neighborhood Search
SS	Scatter Search
NML	Next Machine Load
EDA	Estimation of Distribution Analysis