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A Review for Dynamic Scheduling in Manufacturing

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A Review for Dynamic Scheduling in Manufacturing

Khalid Muhamadin Mohamed Ahmed Bukkur [α], M.I. Shukri [σ] & Osama Mohammed Elmardi [ρ]

Abstract- This paper discusses review of literature of dynamic scheduling in manufacturing. First, the problem is defined. The scheduling problems are classified based on the nature of the shop configuration into five classes, i.e., single machine, parallel machines, flow shop, job shop, and open shop. A variety of approaches have been developed to solve the problem of dynamic scheduling. Dynamic scheduling could be classified into four categories, completely reactive scheduling, predictive-reactive scheduling, robust predictive-reactive scheduling, and robust pro-active scheduling. It is better to combine together different techniques such as operational research and artificial intelligence to overcome dynamic scheduling problems so as to endow the scheduling system with the required flexibility and robustness, and to suggest various orientations for further work is this area of research.

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I. Introduction

Dynamic scheduling is the process of absorbing the effect of real-time events, analyzing the current status of scheduling and automatically modifying the schedule with optimized measures in order to mitigate disruptions (Amer Fahmya, 2014). Also dynamic scheduling which is named rescheduling and it is the process of updating an existing production schedule in response to disruptions or other change (HERRMANN, 2006). Also dynamic scheduling is a direct allocation of tasks to resources, according to given sequencing rules (Kalinowski Krzyszt of 2013). Real-world scheduling problems are combinatorial, dynamic and stochastic (Daria Terekhov, 2010). The goal in such problems is to determine an approach that dictates, at every decision epoch, how the available resources should be allocated among competing job requests in order to optimize the performance of the system (Daria Terekhova, 2014). Real world scheduling requirements are related with complex systems operated in dynamic environments. That make the current schedules easily outdated and unsuitable (A. Madureira, 2014). In a more general way, dynamic changes can be seen as a set of inserted and cancelled constraints (I. Pereira 2013). The dynamic scheduling problems that our work about are characterized by a stream of products that should produce stochastically over time. Each product requires a combination of resources, sequentially and/or in parallel, for different processing times. The overall aim of our work is to show how dynamic scheduling problem was solved and determined the best ways for dealing with this problem.

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II. Dynamic Scheduling Problems

a) *Definition of dynamic scheduling problems*

A dynamic scheduling problem is generally viewed as a collection of linked static problems (Daria Terekhov, 2010) . Scheduling in manufacturing is an activity of allocating jobs to resources with respect to a time frame that considers critical ratio and considered as N-P hard type of problem (Tarun Kanti Jana, 2013). The main problem in job-shop and flexible job-shop scheduling is that of obtaining the best possible schedules with optimal solutions (Ahmad Shahrizal Muhamad, 2011). There is a need to incorporate these dynamic events into the scheduling process, in order to ensure feasibility of the scheduling plan that the manufacturing system is following (Gomes, 2014). Real-time scheduling theory has traditionally focused upon the development of algorithms for feasibility analysis (determining whether all jobs can complete execution by their deadlines) and run-time scheduling (generating schedules at run-time for systems that are deemed to be feasible) of such systems (Joseph Y-T. Leung"Sanjoy Baruah 2004). The problem of scheduling in the presence of real time events, termed dynamic scheduling. Real-time events have been classified into two categories.

Resource-related: Machine breakdown, operator illness, unavailability or tool failures, loading limits, delay in the arrival or shortage of materials, defective material (material with wrong specification), etc.

Job-related: Rush jobs, job cancellation, due date changes, early or late arrival of jobs, change in job priority, changes in job processing time, etc. (Djamila Ouelhadj, 2008). Also (A. S. Santos, 2014), (Ouelhadj D., 2009) and (Chao Lu, 2017b) agree with that categories.

b) *Scheduling problem classifications*

Suppose that (m) machines $M_j\left(j=1,\ldots,m\right)$ have to process (n) jobs $J_i\left(i=1,\ldots.n\right)$. A schedule for each job is an allocation of one or more time intervals to one or more machines (Brucker, 2007). The scheduling problems are classified based on the nature of the shop configuration into five classes, i.e., single machine, parallel machines, flow shop, job shop, and open shop(J.Behnamian 2014)(Eliana María González-Neira, 2017).

c) *Optimality criteria (objective functions)*

We denote the finishing time of job J_i by C_i, and the associated cost by $f_i(C_i)$. There are essentially two types of total cost functions.

$$f_{\max}(C) := \max\{\langle f_i(C_i) | i = 1,\ldots,n\rangle\}$$

and

$$\sum f_i(C) := \sum_{i\ 1}^{n} f_i(C_i)$$

Called bottleneck objectives and sum objectives, respectively. The scheduling problem is to find a feasible schedule which minimizes the total cost function. If the functions f_i are not specified, we set $\gamma = f_{\max}$ or $\gamma = \sum f_i$. However, in most cases we consider special functions f_i. The most common objective functions are that make span $\max\{C_i \mid i = 1,\ldots,n\}$, total flow time $\sum_{i=1}^{n} C_i$, and weighted (total) flow time $\sum_{i=1}^{n} w_i C_i$. In this case we write $\gamma = C_{\max}, \gamma = \sum C_i, \gamma = \sum w_i C_i$, respectively. Other objective functions depend on due dates d_i which are associated with jobs J_i. We define for each job J_i:

$L_i := C_i - d_i$ lateness

$E_i := \max\{0, d_i - c_i\}$ earliness

$T_i := \max\{0, C_i - d_i\}$ tardiness

$D_i := |C_i - d_i|$ absolute deviation

$S_i := (C_i - d_i)^2$ squared deviation

$U_i := 0 if C_i \le d_i$, 1 otherwise unit penalty.

With each of these functions G_i we get four possible objectives $\gamma = \max G_i, \max w_i G_i, \sum G_i, \sum w_i G_i$. The most important bottleneck objective besides $C_{\max}$ is maximum lateness $L_{\max} := \max L_i$. Other objective functions which are widely used are $\sum T_i, \sum w_i T_i, \sum U_i, \sum w_i U_i, \sum D_i, \sum w_i D_i, \sum S_i, \sum w_i S_i, \sum E_i, \sum w_i E_i$. Linear combinations of these objective functions are also considered. An objective function which is non decreasing with respect to all variables C_i is called regular. Functions involving E_i, D_i, S_i are not regular. The other functions defined so far are regular. A schedule is called active if it is not possible to schedule jobs (operations) earlier without violating some constraint. A schedule is called semi active if no job (operation) can be processed earlier without changing the processing order or violating the constraints(Brucker, 2007).

Practical experience shows that some computational problems are easier to solve than others. Complexity theory provides a mathematical framework in which computational problems are studied so that they can be classified as "easy" or "hard". One of the main issues of complexity theory is to measure the performance of algorithms with respect to computational time. A problem is called polynomially (P) solvable if there exists a polynomial p such that $T(|x|) \in O(p(|x|))$ for all inputs x for the problem, i.e. if there is a k such that $T(|x|) \in O(|x|^k)$(Jun Zhao, 2014). A commonly faced problem in flow-shop scheduling is that it belongs to the class of NP-hard problems (Florian T. Hecker, 2014). We are dealing with scheduling problems which are not decision problems, but optimization problems. An optimization problem is called NP-hard if the corresponding decision problem is NP-complete. A decision problem P is NP-complete in the strong sense if P belongs to NP and there exists a polynomial q for which Pq is NP-complete (Chuanli Zhao, 2017) . The knowledge that a scheduling problem is NP-hard is little consolation for the algorithm designer who needs to solve the problem. Fortunately, despite theoretical equivalence, not all NP-hard problems are equally hard from a practical perspective. We have seen that some NP-hard problems can be solved pseudo polynomially using dynamic programming. Another possibility is to apply approximation algorithms. One of the most successful methods of attacking hard combinatorial optimization problems is the discrete analog of "hill climbing", known as local (or neighborhood) search. Any approach without formal guarantee of performance can be considered a "heuristic". Such approaches are useful in practical situations if no better methods are available (Brucker, 2007).

III. Current Dynamic Scheduling Approaches

Dynamic scheduling divided into four categories, completely reactive scheduling, predictive-reactive scheduling, robust predictive-reactive scheduling, and robust pro-active scheduling (Ouelhadj D., 2009). In (Amer Fahmya, 2014) and (Djamila Ouelhadj, 2008) there are three main dynamic scheduling categories (or strategies),completely reactive scheduling, robust pro-active scheduling, predictive-reactive scheduling.

a) Completely reactive scheduling

In completely reactive scheduling no firm schedule is generated in advance and decisions are made locally in real-time. A dispatching rule is used to select the next job with highest priority to be processed from a set of jobs awaiting service at a machine that becomes free (Ouelhadj D., 2009). This scheduling type termed as "Dispatching" or "Priority Rule-based Scheduling". This approach was introduced by(Dongjuan, 2010) who proposed a dynamic scheduling established through an aloging connectivity. A new policy proposed for scheduling systems with setups, the Hedging Zone Policy (HZP) policy belongs to what we called the Clearing Cruising (CC) Class, which includes all produce-up-to or base stock policies (Tubilla, 2011). There was another work presented deal with dynamic task allocation mechanism for machine scheduling in a job shop environment following agent based holonic control approach. (Tarun Kanti Jana 2013). A new optimization-based control algorithm was proposed that developed for the buffer management and the production scheduling of a multiple-line production plant (Andrea Cataldo 2015). An approach to dynamically adjust the parameters of a dispatching rule was presented depending on the current system conditions by using machine learning method and demonstrate the capability of their work by reducing the mean tardiness of job (Heger, 2016). There was another article deals with a parallel machine scheduling problem subject to non-interference constraints. The good results presented by the heuristic enable the evaluation of different storage policies for real size instances (Gabriela N. Maschiettoa 2016). A work of a multi- agent-based dynamic scheduling system was introduce for manufacturing flow lines (MFLs) using the Prometheus methodology (PM) considering the dynamic customer demands and internal disturbances. The proposed decision making system supports both static and dynamic scheduling (Ali Vatankhah Barenji, 2016). A complex manufacturing network model CMNBS was proposed for RFID "radio frequency identification" -driven DMS" discrete manufacturing system" modeling, performance analyzing and dynamic scheduling (Jiewu Leng, 2017). There was another work, a simulated annealing and the dispatching rule based complete rescheduling approaches as well as the simulation optimization tools are proposed for dynamic identical parallel machines scheduling problem with a common server (Alper Hamzadayi 2016). There was another work considered the problem of optimizing on-line the production scheduling of a multiple-line production plant (Andrea Cataldo, 2015).

b) Robust pro-active scheduling

This scheduling approach is based on building predictive schedules with studying the main causes of disruptions and integrating them into the schedules. The disruptions are measure based on actual completion measures compared to the originally planned completions; then the mitigation of these disruptions was mitigated through simple adjustment to the activities durations(Ouelhadj D., 2009). An algorithm was developed for the optimal production schedule in a backward dynamic programming approach. It will be applied to the development of an algorithm for production scheduling problems which permit backlogging (C. S. SUNG 1987).

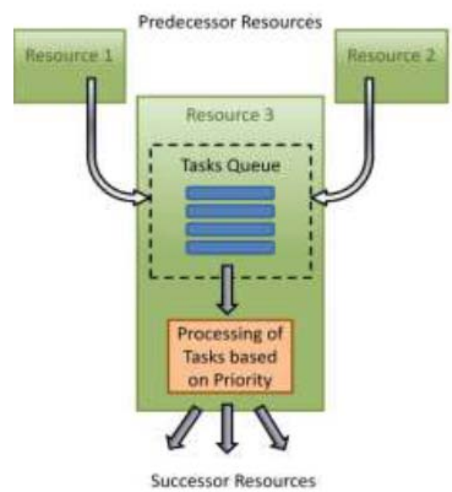

Figure 1: Completely reactive scheduling

There was another work proposed a new neural network approach to solve the single machine mean tardiness scheduling problem and the minimum make spanjob shop scheduling problem. The proposed network combines the characteristics of neural networks and algorithmic approaches (Ihsan Sabuncuoglu 1996).A scheduling approach that uses and compares inductive learning and neural networks was presented to improve the manufacturing system's performance (PAOLO PRIORE, 2001). A scheduling method based on variable neighborhood search (VNS) was proposed for dynamic job shop scheduling problem with random job arrivals and machine breakdowns (M. A.Adibi 2010).A multi-agent based approach is developed in another work to solve the part scheduling problem in multiple job shop cells with inter cell moves and flexible routes.A pheromone based approach (PBA) using multi agent is presented in this work, in which various types of pheromone inspired by ant colony optimization (ACO) are adopted as the basis of negotiation among agents (Dongni Li 2013). (Yiping Wen 2014) Proposeda schedulingoptimization algorithm named PACO-TCbyutilizing the theory of ant colony optimization. (Zaki Ahmad Khan, 2017) Also propose dynamic task scheduling algorithm. The comparative simulation study shows that the proposed algorithm gives better performance in terms of task scheduling on various cube based multiprocessor networks.(Zhicheng Cai 2017) This study presenteda bag-based delay scheduling strategy and a single-type based virtual machine interval renting method to decrease the resource renting cost. (Mehdi Abedi, 2017) Proposed a new mathematical modelto study scheduling with simultaneously consideration of aging effects and multi maintenances on un-related parallel machine problem in just in time environment.

c) Predictive-reactive scheduling

Predictive-reactive scheduling is the most common dynamic scheduling approach used in manufacturing systems. Most of the definitions reported in the literature on dynamic scheduling refer to predictive-reactive scheduling.

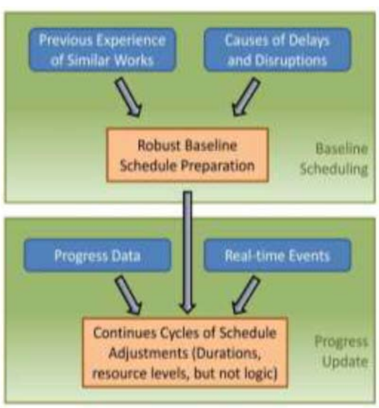

Figure 2: Robust pro-active scheduling

Predictive-reactive scheduling is a scheduling/ rescheduling process in which schedules are revised in response to real-time events. Predictive-reactive scheduling is a two step process. First, a predictive schedule is generated in advance with the objective of optimizing shop performance without considering possible disruptions on the shop floor. This schedule is then modified during execution in response to real-time events(Ouelhadj D., 2009).(Abdallah Elkhyari, 2003) Introduced a new approach for solving dynamic RCPSP "Resource Constrained Project Scheduling Problem" instances. This work is based on new constraint programming techniques. And provided a complete system able to handle both dynamic and over-constrained scheduling problems. (Chuanyu Zhao, 2013) Proposed a novel and rigorous RDHS "real-time dynamic hoist Scheduling " methodology , which takes into account uncertainties of new coming jobs and targets real-time scheduling optimality and applicability. (Bing-hai Zhou, 2013) Proposed a dynamic scheduling method of the photolithography process based on kohonen neural network. It determines the optimal combination of scheduling policies due to the special system status. (Gomes, 2014) Stated that dynamic events must be taken into account, since they may have a major impact on the schedule. They can change the system status and affect performance. Manufacturing systems require immediate response to these dynamic events. (Paolo Priore, 2015) Stated that dispatching rules are usually applied to schedule jobs in Flexible Manufacturing Systems (FMSs) dynamically. A scheduling approach that employs Support Vector Machines (SVMs) and case-based reasoning (CBR) was proposed.(Yuxin Zhai 2017) Proposed adynamic scheduling approach to minimize the electricity cost of a flow shop with a grid-integrated wind turbine. (Chao Lu, 2017b)There was another work developed a high-performance multi-objective predictive-reactive scheduling method for this MODWSP in order to narrow the gap between theoretical research and applicable practice.

d) Robust pro-active scheduling

This scheduling approach is based on building predictive schedules with studying the main causes of disruptions and integrating them into the schedules; which, predictably, can accommodate changes in a dynamic environment. The disruptions are measured based on actual completion measures compared to the originally planned completions.(Amer Fahmya, 2014)

e) Comparison of dynamic scheduling approaches

Dynamic scheduling has been defined under four categories: on-line scheduling (completely reactive approaches), predictive-reactive scheduling, robust predictive-reactive scheduling, and robust pro-active scheduling. In completely reactive scheduling, schedules are easily generated using dispatching rules. However, the solution quality is poor due to the nature of these rules. Predictive-reactive scheduling is the most common approach in dynamic scheduling. Predictive reactive approaches search in a larger solution space, generate high quality schedules, and can generate better system performance to increase productivity and minimize operating costs compared with on-line scheduling and predictive scheduling. Simple schedule adjustments require little effort and are easy to implement. However, they may lead to poor system performance. Generating robust schedules lead to better system performance, even though robustness measures are not easy to define.

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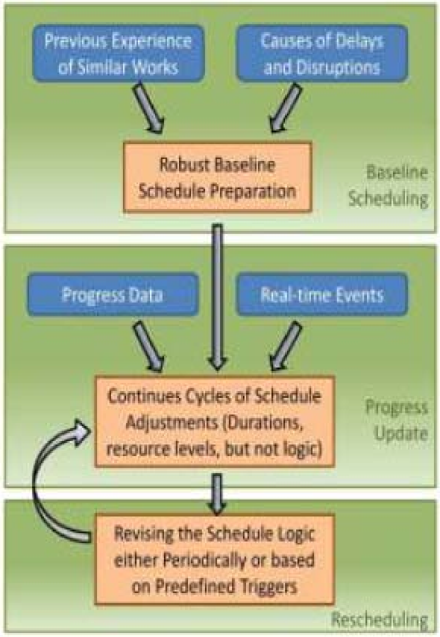

Figure 3: Predictive-reactive scheduling

IV. Dynamic Scheduling Techniques Applied to Manufacturing Systems

There are many techniques that used for solving dynamic scheduling in manufacturing systems and they vary. Here we discuss techniques like "Dispatching rules, Heuristics Techniques, Meta-heuristics Techniques, Hyper-heuristics techniques, Artificial Intelligence Techniques, Multi-agent-based Dynamic Scheduling, The model of network topology technique, Constraint programming technique, Enviro-nment driven, function-based technique".

a) *Dispatching rules*

Dispatching rules have played a significant role within dynamic contexts. (Ouelhadj D., 2009). From the literature reviewed, Dispatching heuristic was able to provide not only a good solution but also the best solutions for the system observed (Kaban, 2012). Dispatching rules are quick but lack robustness and adaptability(Atif Shahzad, 2016). (Edna Barbosa da Silva, 2014) In this work, a simulation model was proposed to evaluate sequencing solutions and present a simulation study of dispatching rules in stochastic job shop dynamic scheduling. (Atif Shahzad, 2016) Stated that dynamic scheduling uses priority dispatching rule (PDR) to prioritize jobs waiting for processing at a resource.

b) *Heuristics techniques*

Heuristics are problem specific schedule repair methods, which do not guarantee to find an optimal schedule, but have the ability to find reasonably good solutions in a short time. The most common schedule repair heuristics are: right-shift schedule repair, match-up schedule repair, and partial schedule repair (Ouelhadj D., 2009). Dispatching rules are also heuristics that have played a significant role in completely reactive scheduling. And used in real-time to select the next job waiting for processing at a resource (Djamila Ouelhadj, 2008). (JurgenBranke 2016) In this work constitutes the first comprehensive review of hyper-heuristics for the automated design of production scheduling heuristics, providing a simple taxonomy and focusing on key design choices such as the learning method, attributes, representation and fitness evaluation. (Andrea Rossi, 2013).

c) *Meta-heuristics Techniques*

Meta-heuristics (tabu search, simulated annealing, the ant colony algorithm, bee colony and genetic algorithms) have been successfully used to solve production scheduling problems (Ouelhadj D., 2009). Meta-heuristics have been widely used to solve static deterministic production scheduling. However, little research work has addressed the use of meta-heuristics in dynamic scheduling (Djamila Ouelhadj, 2008). Tabu search algorithm is the alternative approaches to the modern meta-heuristic optimization techniques (Balicki, 2007) . In this work a framework for multi objective bee colony optimization is proposed to schedule batch jobs to available resources where the number of jobs is greater than the number of resources (Sana Alyaseri, 2013) . Ant Colony Optimization (ACO) is a meta-heuristic technique and is used to find shortest path between source and destination (Sahana et al., 2014) . The ant colony algorithm is a new method to deal with the rescheduling problem of observing spacecraft (Li Yuqing 2014) . In this work, an efficient an improved ant colony optimization IACO is proposed for flexible job shop scheduling problem FJSP in order to minimize make span(Lei Wang, 2017) .There was another method proposed that makes use of the greedy randomized adaptive search procedure (GRASP) also used to solve dynamic scheduling problems (Adil Baykasoğlu, 2017).Also, a hybrid genetic and simulated annealing algorithms is developed because of the high potential of outcomes to be trapped in the local optima (Aidin Delgoshaei, 2016). As solution approaches, two meta-heuristic solution approaches based on the simulated annealing (SA) algorithm and the discrete particle swarm optimization (DPSO) are proposed to obtain a near optimal solution in a reasonable amount of time (Byung Jun Joo, 2015). There was another work proposed a GA for solving the agile job shop scheduling to minimize the make span(Li and Chen, 2010). Also in this work, an implementation of a standard GA (SGA) to solve the task scheduling problem has been presented (Omara and Arafa, 2010). A genetic algorithm approach is applied to hypothetical numerical examples with the objective of minimizing the makespan in the work of (C. S.Wong, 2013).

d) Hyper-heuristics techniques

Hyper-heuristics are defined as "an automated methodology for selecting or generating heuristics to solve hard computational search problems" (Jurgen Branke, 2016). There was another work developed a two-stage hyper-heuristic to automatically generate sets of dispatching rules for complex and dynamic scheduling problems. The approach combines a GP hyper-heuristic that evolves a composite rule from basic attributes (Christoph W. Pickardt, 2013). There was another study used a hybrid heuristic model combining both Genetic Algorithm (GA) and Fuzzy Neural Network (FNN) (Alper Seker, 2013). This work introduces a two-phase hybrid solution method. The first phase relies on solving a series of linear programming problems to generate an initial solution. In the second phase, a variable neighborhood descent procedure is applied to improve the solution (Amina Lamghari, 2014). This work presented a Greedy Randomized Adaptive Search Procedure (GRASP)-Mixed Integer Programming (MIP) hybrid algorithm for solving the precedence constrained production scheduling problem (PCPSP) of mine optimization (Angus Kenny, 2017). For solving a multi-objective optimization problem, a mathematical model formulated and a new hybrid multi-objective backtracking search optimization algorithm developed with an energy saving scenario (Chao Lu, 2017a). A dynamic and heterogeneous hybrid Architecture for Optimized and Reactive Control, ORCA, was introduced and applied to the manufacturing scheduling of an FMS (Cyrille Pach, 2014).

e) Artificial intelligence techniques

A number of dynamic scheduling problems have adopted artificial intelligence techniques such as knowledge-based-systems, neural networks, case-based reasoning, fuzzy logic, Petri nets, etc. (Banu Çaliş 2013). (LIXIN TANG 2005)(T. Eguchi, 1999) In this works a neural network approach was proposed to a dynamic job shop scheduling problems. There was another work present a survey of the use of an AI technique, in various manufacturing systems (Kumar, 2014). To derive better dynamic scheduling systems, some researchers developed hybrid systems which combine various artificial intelligence techniques (Binodini Tripathy, 2015).

f) Multi-agent-based dynamic scheduling

To optimize performance, scheduling decisions are made centrally at the level of the supervisor, and then distributed to the manufacturing resource level for execution(Kaminsky, 2006). In the present work, Multi-agents was proposed to find the near optimal solution for job shop scheduling problem using GA and VNS approach in parallel (Rakesh Kumar, 2016).

g) The model of network topology technique

A contribution made towards solving the problem of dynamic scheduling on parallel machines by introducing a model of network topology technique which captures some important aspects of the practical scheduling problem (Anja Feldmann 1994).

h) Constraint programming technique

Recently, Constraint Programming (CP) attracts a high interest among both planning and scheduling community. It was based on the idea of describing the problem declaratively by means of constraints, logical relations among several unknowns (or variables), and, consequently, finding a solution satisfying all the constraints (Barták, 1999).

i) Environment driven, function-based technique

In this technique, an environment driven, function-based was developed for solving the dynamic single-machine scheduling problem. This technique can capture uncertainty and dynamic characteristics associated with the dynamic environment. (Arezoo Atighehchian 2013). There is another work proposes an innovative approach to study the dynamic scheduling problem in FMS, taking the objectives of minimum or maximum energy consumption into account (Liping Zhang, 2013).

j) Comparison of dynamic scheduling techniques

In order to ascertain the value of the various solution techniques, there has been some published work comparing some of these techniques. Heuristics have been widely used to react to the presence of real-time events because of their simplicity, but they may become stuck in poor local optima. To overcome this, meta heuristics such as tabu search, simulated annealing, and genetic algorithms have been proposed. Several comparative studies have been provided in the literature to compare the performance of tabu search, genetic algorithms, and simulated annealing. Unlike simulated annealing and tabu search based on manipulating one feasible solution, genetic algorithms manipulate a population of feasible solutions. Genetic algorithms were found not efficient to find a near-optimal solution in a reasonable time compared to tabu search and simulated annealing which operate on a single configuration and not on an entire population. Knowledge-based systems possess the potential for automating human expert reasoning and heuristic knowledge to run production scheduling systems. In terms of effectiveness of the decision-making capability, knowledge-based systems are limited by the quality and integrity of the specific domain knowledge. Fuzzy logic has not yet been explored to its fullest potential. Neural networks cannot guarantee to provide optimal decisions, but their learning capability makes them ideally suited for rapidly changing systems. Integrating neural networks, simulation, and expert systems seems to have a lot of promise. In addition, in developing practical integrated dynamic scheduling systems, it is necessary to combine together different techniques such as operational research and artificial intelligence to endow the scheduling system with the required flexibility and robustness (Djamila Ouelhadj, 2008). In order to give recommendations on when it is beneficial to use a hyper-heuristic and how to design it, extensive and meaningful performance comparisons of evolved heuristics with more sophisticated (global) solution algorithms as well as between different hyper-heuristics are needed. So far, such comparisons have been rather limited hyper-heuristic approaches have strengths compared to global optimization approaches in particular in dynamic and stochastic environments where a quick reaction is important. They also become more competitive as the problem size (and thus the search space for the global optimizer) increases. One reason for the limited number of comparisons may be that hyper-heuristics possess several properties that make a fair comparison particularly difficult. For example, not only are the hyper-heuristics stochastic algorithms with many parameters to tune, but also is the evaluation function often a stochastic simulation, resulting in stochastic fitness values. Also, the running time for the simulations can be quite substantial, and, to make things worse, the running time to evaluate a particular dispatching rule strongly depends on the rule itself, as the time to calculate the priority value and the numbers of jobs in the system depend on the rule itself. This implies that a comparison of hyper heuristics based on the same number of function evaluations has limited validity (Jurgen Branke, 2016). For The network topology technique there was a question which remain open were, how can the model be extended to capture the practical scheduling even better? and if the competitive ratio is the right performance measurement? also of interest is whether randomization can help to improve the performance of the scheduling algorithm (Anja Feldmann 1994). About constraints programming despite of studying the proposed framework using the complex process environment background we believe that the results are applicable in general to other (non- production) problem areas where mixed planning and scheduling capabilities are desirable (Barták, 1999). The efficiency of the function-based approach is evaluated against the most commonly used dispatching rules. Moreover, the proposed approach is compared with an agent-based approach, which employs the Q-learning algorithm to develop a decision-making policy. Experimental results show that the proposed approach is an effective method for dynamic single-machine scheduling (Arezoo Atighehchian 2013).

V. Results and Discussion

A dynamic scheduling is not dissection making problem but it is optimization problem. And it concerns with resources available, the jobs that should be done and the perfect time to do jobs. In manufacturing operations there should be an optimum utilization between resources and jobs in minimum time to gain markets. I think that a dynamic scheduling is a good way to solve any problem of scheduling in the presence of real-time events for allocating jobs to resources in manufacturing. From the above we can define dynamic scheduling like this "A dynamic scheduling is the optimum Utilization between resources and jobs in real time events ". Predictive-reactive scheduling is the most common approach in doing dynamic scheduling. It searches in a larger solution space, generate high quality schedules, and can generate better system performance to increase productivity and minimize operating costs compared with on-line scheduling and predictive scheduling. In computational complexity sense optimization problems belongs to the class of NP-hard problems. Not all NP-hard problems are equally hard from a practical perspective. We have seen that some NP-hard problems can be solved pseudopolynomially using dynamic programming or “hill climbing”, known as local (or neighborhood) search Dynamic scheduling has been solved using many techniques. It is necessary to combine together different techniques such as operational research and artificial intelligence to endow the scheduling system with the required flexibility and robustness for example integrating neural networks, simulation, and expert systems or a hybrid approach. I think that dynamic scheduling has a main role in developing the fourth industrial revolution.

VI. Conclusion and the Research Opportunities

A Dynamic scheduling is the optimum Utilization between resources and jobs in real time events. The scheduling problems were classified based on the nature of the shop configuration into five classes. Dynamic scheduling divided into four categories. Predictive-reactive scheduling is the most common approach. In computational complexity sense optimization problems belongs to the class of a NP-hard problems, practical experience shows that some computational problems are easier to solve than others. To solve dynamic scheduling, it is necessary to combine together different techniques such as operational research and artificial intelligence. Further work in this topic is expected to investigate the role of dynamic scheduling in manufacturing systems in Industry 4.0"the fourth industrial revolution", and as a core element of systems engineering, also doing dynamic scheduling as a program in the embedded systems in manufacturing environment

References Références Referencias

1. A. Madureira, I. P., P. Pereira, A. Abraham, 2014. Negotiation Mechanism for Self-Organized Scheduling System with Collective Intelligence. Neurocomputing, 132, 97-110.
2. A. S. Santos, M. L. R. V., G. D. Putnik .A. M. Madureira 2014. Alternative Approaches Analysis for Scheduling in an Extended Manufacturing Environment. Ieee
3. Abdallah Elkhyari, C. G., Narendra Jussien 2003. Constraint Programming for Dynamic Scheduling Problems. Http://Www.Emn.Fr/Jussien/Publications.
4. Adil Baykasoğlu, F. S. K. 2017. Solving Comprehensive Dynamic Job Shop Scheduling Problem by using a Grasp-Based Approach. International Journal of Production Research, 55, 3308-3325.
5. Ahmad Shahrizal Muhamad, S. D. 2011. An Artificial Immune System for Solving Production Scheduling Problems: A Review. Artificial Intelligence Review, 39, 97-108.
6. Aidin Delgoshaei, A. A., Mohd Khairol Anuar Ariffin, Chandima Gomes, 2016. A Multi-Period Scheduling of Dynamic Cellular Manufacturing Systems in the Presence of Cost Uncertainty. Computers & Industrial Engineering, 100, 110-132.
7. Ali Vatankhah Barenji, R. V. B., Danial Roudi , Majid Hashemipour 2016. A Dynamic Multi-Agent-Based Scheduling Approach for Smes. The International Journal of Advanced Manufacturing Technology, 89, 3123-3137.
8. Alper Hamzadayi, G. Y. 2016. Event Driven Strategy Based Complete Rescheduling Approaches for Dynamic M Identical Parallel Machines Scheduling Problem with a Common Server. Computers & Industrial Engineering, 91, 66-84.
9. Alper Seker, S. E., Reha Botsali, 2013. A Neuro-Fuzzy Model for A New Hybrid Integrated Process Planning and Scheduling System. Expert Systems with Applications, 40, 5341-5351.
10. Amer Fahmya, T. M. H., Hesham Bassionic 2014. what is Dynamic Scheduling? Pm World Journal, Vol. Iii, 9.
11. Amina Lamghari, R. D. J. A. F. 2014. A Hybrid Method Based on Linear Programming And Variable Neighborhood Descent for Scheduling Production in Open-Pit Mines. Journal of Global Optimization, 63, 555-582.
12. Andrea Cataldo, A. P., Riccardo Scattolini 2015. Production Scheduling of Parallel Machines with Model Predictive Control. Control Engineering Practice, 42, 28-40.
13. Andrea Cataldo, A. P., Riccardo Scattolini, 2015. Production Scheduling of Parallel Machines with Model Predictive Control. Control Engineering Practice, 42, 28-40.
14. Andrea Rossi, A. P., Michele Lanzetta, 2013. Dynamic Set-Up Rules for Hybrid flow Shop Scheduling With Parallel Batching Machines. International Journal of Production Research, 52, 3842-3857.
15. Angus Kenny, X. L., Andreas T. Ernst, Dhananjay Thiruvady, 2017. Towards Solving Large-Scale Precedence Constrained Production Scheduling Problems in Mining. Gecco, 1137-1144.
16. Anja Feldmann, J. S., Shang-Hua Teng 1994. Dynamic Scheduling on Parallel Machines. Theoretical Computer Science 130, 24.
17. Arezoo Atighehchian, M. M. S. 2013. An Environment-Driven, Function-Based Approach to Dynamic Single-Machine Scheduling. European J. Industrial Engineering, Vol. 7, 19.
18. Atif Shahzad, N. M. 2016. Learning Dispatching Rules for Scheduling: A Synergistic View Comprising Decision Trees, Tabu Search and Simulation. Computers, 5, 3.
19. Balicki, J. 2007. Tabu Programming For Multiobjective Optimization Problems. Ijcsns International Journal of Computer Science And Network Security Vol. 7.
20. Banu Çaliş, S. B. 2013. A Research Survey: Review of Ai Solution Strategies of Job Shop Scheduling Problem. Journal of Intelligent Manufacturing, 26, 961-973.
21. Barták, R. 1999. Dynamic Constraint Models for Planning And Scheduling Problems. Grant Agency.
22. Bing-Hai Zhou, X. L., Richard. Y. K.Fung 2013. Dynamic Scheduling Of Photolithography Process Based on Kohonen Neural Network. Journal of Intelligent Manufacturing, 26, 73-85.
23. Binodini Tripathy, S. D., Sasmita Kumari Padhy, 2015. Dynamic Task Scheduling using A Directed Neural Network. Journal of Parallel And Distributed Computing, 75, 101-106.
24. Brucker, P. 2007. Scheduling Algorithms, Verlag Berlin Heidelberg Springer.
25. Byung Jun Joo, P. X. 2015. A Production Scheduling Problem with Uncertain Sequence-Dependent Set-Up Times and Random Yield. International Journal of Production Research, 53, 2820-2835.
26. C. S. Sung, J. T. R. 1987. A Dynamic Production Scheduling Model With Lost-Sales or Backlogging. Comput. Opns Res., 14, 8.
27. C. S.Wong, F. T. S. C., S. H. Chung, 2013. A Joint Production Scheduling Approach Considering Multiple Resources and Preventive Maintenance Tasks. International Journal of Production Research, 51, 883-896.

28. Chao Lu, L. G., Xinyu Li, Quanke Pan,Qi Wang, 2017a. Energy-Efficient Permutation flow Shop Scheduling Problem using a Hybrid Multi-Objective Backtracking Search Algorithm. Journal of Cleaner Production, 144, 228-238.
29. Chao Lu, L. G., Xinyu Li, Shengqiang Xiao, 2017b. A Hybrid Multi-Objective Grey Wolf Optimizer for Dynamic Scheduling in a Real-World Welding Industry. Engineering Applications of Artificial Intelligence, 57, 61-79.
30. Christoph W. Pickardt, T. H., Jurgen Branke, Jens Heger, Bernd Scholz-Reiter, 2013. Evolutionary Generation of Dispatching Rule Sets For Complex Dynamic Scheduling Problems. International Journal of Production Economics, 145, 67-77.
31. Chuanli Zhao, F. J., T. C. E. Cheng, Min Ji, 2017. A Note on the Time Complexity of Machine Scheduling with Dejong's Learning Effect. Computers & Industrial Engineering, 112, 447-449.
32. Chuanyu Zhao, J. F., Qiang Xu 2013. Real-Time Dynamic Hoist Scheduling for Multistage Material Handling Process Under Uncertainties. Aiche Journal, 59, 465-482.
33. Cyrille Pach, T. B., Therese Bonte, Damien Trentesaux, 2014. Orca-Fms: A Dynamic Architecture for the Optimized and Reactive Control of Flexible Manufacturing Scheduling. Computers in Industry, 65, 706-720.
34. Daria Terekhov, J. C. B., Tony T. Tran 2010. Integrating Scheduling And Queueing for Dynamic Scheduling Problems.
35. Daria Terekhova, D. G. D. A. J. C. B. 2014. Queueing-Theoretic Approaches for Dynamic Scheduling: A Survey.
36. Djamila Ouelhadj, S. P. 2008. A Survey of Dynamic Scheduling In Manufacturing Systems. Journal of Scheduling, 12, 417-431.
37. Dongjuan, X. 2010. A Dynamic Scheduling Model Oriented to Flexible Production. Ieee International Coriference on Educational and Network Technology
38. Dongni Li, Y. W., Guangxue Xiao, Jiafu Tang 2013. Dynamic Parts Scheduling in Multiple Job Shop Cells Considering Intercell Moves And Flexible Routes. Computers & Operations Research, 40, 1207-1223.
39. Edna Barbosa Da Silva, M. G. C., Marilda F´Atima De Souza Da Silva, Fabio Henrique Pereira 2014. Simulation Study of Dispatching Rules In Stochastic Job Shop Dynamic Scheduling. World Journal of Modelling and Simulation, .Vol. 10 11.
40. Eliana María González-Neira, A. R. M.-T., David Barrera, 2017. Flow-Shop Scheduling Problem under Uncertainties: Review and Trends. International Journal of Industrial Engineering Computations, 399-426.
41. Florian T. Hecker, M. S., Thomas Becker, Bernd Hitzmann, 2014. Application of A Modified Ga, Aco and a Random Search Procedure to Solve the Production Scheduling of A Case Study Bakery. Expert Systems with Applications, 41, 5882-5891.
42. Gabriela N. Maschiettoa, Y. O., Martin G. Ravetti, Mauricio C. De Souza, Farouk Yalaouib 2016. Crane Scheduling Problem With Non-Interference Constraints in A Steel Coil Distribution Center. International Journal of Production Research.
43. Gomes, S. R. P. 2014. Selection Constructive Based Hyper-Heuristic for Dynamic Scheduling. Master Degree.
44. Heger, J., Branke, Jurgen, Hildebrandt, Torsten, Scholz-Reiter, Bernd. 2016. Dynamic Adjustment of Dispatching Rule Parameters in flow Shops With Sequence Dependent Setup Times. International Journal of Production Research.
45. Herrmann, J. W. 2006. Handbook of Production Scheduling University of Maryland, College Park, Sprineger.
46. I. Pereira , A. M. 2013. Self-Optimization Module For Scheduling Using Case-Based Reasoning.
47. Ihsan Sabuncuoglu, B. G. 1996. A Neural Network Model For Scheduling Problems. European Journal of Operational Research 93, 12.
48. J.Behnamian, S. M. T. F. G. 2014. A Survey of Multi-Factory Scheduling. Journal of Intelligent Manufacturing, 27, 231-249.
49. Jiewu Leng, P. J. 2017. Dynamic Scheduling in Rfid-Driven Discrete Manufacturing System by using Multi-Layer Network Metrics As Heuristic Information. Journal of Intelligent Manufacturing.
50. Joseph Y-T. Leung"Sanjoy Baruah, J. G. 2004. Handbook of Scheduling. Scheduling Real-Time Tasks: Algorithms And Complexity, Usa, Crc Press Llc.
51. Jun Zhao, W., Kan Sun, Ying Liu 2014. A Bayesian Networks Structure Learning and Reasoning-Based Byproduct Gas Scheduling in Steel Industry. Ieee Transactions on Automation Science and Engineering, Vol. 11,.
52. Jurgen Branke, S. N., Christoph Pickardt, Mengjie Zhang, 2016. Automated Design of Production Scheduling Heuristics: A Review. Ieee Transactions on Evolutionary Computation, 20, 110-124.
53. Jurgenbranke , S. N., Christoph Pickardt , Mengjie Zhang 2016. Automated Design of Production Scheduling Heuristics: A Review. Ieee Transactions on Evolutionary Computation, 20, 110-124.
54. Kaban, A. K., Othman, Z, Rohmah, D. S. 2012. Comparison of Dispatching Rules in Job-Shop Scheduling Problem using Simulation: A Case Study. Int J Simul Model (2012), 11, 12.
55. Kalinowski Krzysztof , K. D., Grabowik Cezary 2013. Predictive - Reactive Strategy for Real time

Scheduling of Manufacturing Systems. Applied Mechanics and Materials, 307, 470-473.
56. Kaminsky, P. 2006. Models and Algorithms for Integratedmulti-Stage Production/ Distribution Systems: Third Party Logistics. Nsf Design, Service, Andmanufacturing Grantees and Research Conference, St. Louis,Missouri Grant #Dmi - 0200439.
57. Kumar, V. S., O.J., Soni, G., Kumar, R. 2014. a Review on Artificial Neural Network Approach in Manufacturing Systems. Https://Www.Researchgate.Net/Publication/273695480.
58. Lei Wang, J. C., Ming Li, Zhihu Liu, 2017. Flexible Job Shop Scheduling Problem using an Improved Ant Colony Optimization. Scientific Programming, 2017, 1-11.
59. Li, Y. & Chen, Y. 2010. A Genetic Algorithm for Job-Shop Scheduling. Journal of Software, 5.
60. Li Yuqing , W. R., Xu Minqiang 2014. Rescheduling of Observing Spacecraft using Fuzzy Neural Network and Ant Colony Algorithm. Chinese Journal of Aeronautics, 27, 678-687.
61. Liping Zhang, X. L., Liang Gao, Guohui Zhang, 2013. Dynamic Rescheduling in Fms that is Simultaneously Considering Energy Consumption and Schedule Efficiency. The International Journal of Advanced Manufacturing Technology, 87, 1387-1399.
62. Lixin Tang, W. L., J I Y I N Li U, 2005. A Neural Network Model And Algorithm for the Hybrid Flow Shop Scheduling Problem in a Dynamic Environment. Journal of Intelligent Manufacturing, 16, 361–370, 2005.
63. M. A.Adibi, M. Z., M.Amiri 2010. Multi-Objective Scheduling of Dynamic Job Shop using Variable Neighborhood Search. Expert Systems with Applications, 37, 282-287.
64. Mehdi Abedi, H. S., Hamed Fazlollahtabar 2017. Hybrid Scheduling and Maintenance Problem using Artificial Neural Network Based Meta-Heuristics. Journal of Modelling in Management, 00-00.
65. Omara, F. A. & Arafa, M. M. 2010. Genetic Algorithms for Task Scheduling Problem. Journal of Parallel and Distributed Computing, 70, 13-22.
66. Ouelhadj D., P. S. 2009. Survey of Dynamic Scheduling In Manufacturing Systems. Journal of Scheduling, 12., 27.
67. Paolo Priore, D. D. L. F., Raúl Pino, Javier Puente 2001. Dynamic Scheduling of Flexible Manufacturing Systems using Neural Networks and Inductive Learning.
68. Paolo Priore, R. P., Jose Parreño, Javier Puente, Borja Ponte 2015. Real-Time Scheduling of Flexible Manufacturing Systems using Support Vector Machines and Case-Based Reasoning. Journal of Economics, Business And Management,, Vol. 3.
69. Rakesh Kumar, M. A., Haryana 2016. Multi Agents Approach for Job Shop Scheduling Problem using Genetic Algorithm and Variable Neighborhood Search Method. The 20th World Multi-Conference on Systemics, Cybernetics And Informatics Wmsci.
70. Sahana, S. K., Jain, A. & Mahanti, P. K. 2014. Ant Colony Optimization for Train Scheduling: an Analysis. International Journal of Intelligent Systems and Applications, 6, 29-36.
71. Sana Alyaseri, K. R. K.-M. 2013. Multi Objective Bee Colony Optimization Framework for Grid Job Scheduling. the 4th International Conference on Computing and Informatics (Http://Www.Uum.Edu.My).
72. T. Eguchi, F. O., T. Hirai 1999. A Neural Network Approach To Dynamic Job Shop Scheduling. K. Mertins Et Al. (Eds.), Global Production Management.
73. Tarun Kanti Jana, B. B., Soumen Paul, Bijan Sarkar, Jyotirmoy Saha 2013. Dynamic Schedule Execution in an Agent Based Holonic Manufacturing System. Journal of Manufacturing Systems, 32, 801-816.
74. Tarun Kanti Jana, B. B., Soumen Paul, Bijan Sarkar, Jyotirmoy Saha, 2013. Dynamic Schedule Execution in an Agent based Holonic Manufacturing System. Journal of Manufacturing Systems, 32, 801-816.
75. Tubilla, F. 2011. Dynamic Scheduling of Manufacturing Systems with Setups And Random Disruptions. Phd Thesis, Massachusetts Institute of Technology.
76. Yiping Wen, J. L., Zhigang Chen , Buqing Cao 2014. Dynamic Scheduling Optimization for Instance Aspect Handling In Workflows.
77. Yuxin Zhai, K. B., Fu Zhao,John W. Sutherland 2017. Dynamic Scheduling of a Flow Shop With On-Site Wind Generation for Energy Cost Reduction Under Real Time Electricity Pricing. Cirp Annals - Manufacturing Technology, 66, 41-44.
78. Zaki Ahmad Khan, J. S., Mahfooz Alam, 2017. Dynamic Scheduling Algorithm for Variants of Hypercube Interconnection Networks. Indian Journal of Science and Technology, 10, 1-5.
79. Zhicheng Cai, X. L., Ruben Ruiz, Qianmu Li 2017. A Delay-Based Dynamic Scheduling Algorithm for Bag-of-Task Workflows With Stochastic Task Execution Times in Clouds. Future Generation Computer Systems, 71, 57-72.
80. A. Madureira, I. P., P. Pereira, A. Abraham, 2014. Negotiation Mechanism for Self-Organized Scheduling System with Collective Intelligence. Neurocomputing, 132, 97-110.
81. A. S. Santos, M. L. R. V., G. D. Putnik .A. M. Madureira 2014. Alternative Approaches Analysis for Scheduling in an Extended Manufacturing Environment. Ieee.

82. Abdallah Elkhyari, C. G., Narendra Jussien 2003. Constraint Programming for Dynamic Scheduling Problems. Http://Www.Emn.Fr/Jussien/Publications.
83. Adil Baykasoğlu, F. S. K. 2017. Solving Comprehensive Dynamic Job Shop Scheduling Problem by using A Grasp-Based Approach. International Journal of Production Research, 55, 3308-3325.
84. Ahmad Shahrizal Muhamad, S. D. 2011. An Artificial Immune System for Solving Production Scheduling Problems: A Review. Artificial Intelligence Review, 39, 97-108.
85. Aidin Delgoshaei, A. A., Mohd Khairol Anuar Ariffin, Chandima Gomes, 2016. A Multi-Period Scheduling of Dynamic Cellular Manufacturing Systems in the Presence of Cost Uncertainty. Computers & Industrial Engineering, 100, 110-132.
86. Ali Vatankhah Barenji, R. V. B., Danial Roudi , Majid Hashemipour 2016. A Dynamic Multi-Agent-Based Scheduling Approach for Smes. the International Journal of Advanced Manufacturing Technology, 89, 3123-3137.
87. Alper Hamzadayi, G. Y. 2016. Event Driven Strategy Based Complete Rescheduling Approaches for Dynamic M Identical Parallel Machines Scheduling Problem with a Common Server. Computers & Industrial Engineering, 91, 66-84.
88. Alper Seker, S. E., Reha Botsali, 2013. A Neuro-Fuzzy Model for A New Hybrid Integrated Process Planning and Scheduling System. Expert Systems with Applications, 40, 5341-5351.
89. Amer Fahmya, T. M. H., Hesham Bassionic 2014. what is Dynamic Scheduling? Pm World Journal, Vol. Iii, 9.
90. Amina Lamghari, R. D. J. A. F. 2014. A Hybrid Method Based On Linear Programming and Variable Neighborhood Descent for Scheduling Production in Open-Pit Mines. Journal of Global Optimization, 63, 555-582.
91. Andrea Cataldo, A. P., Riccardo Scattolini 2015. Production Scheduling of Parallel Machines with Model Predictive Control. Control Engineering Practice, 42, 28-40.
92. Andrea Cataldo, A. P., Riccardo Scattolini, 2015. Production Scheduling of Parallel Machines with Model Predictive Control. Control Engineering Practice, 42, 28-40.
93. Andrea Rossi, A. P., Michele Lanzetta, 2013. Dynamic Set-Up Rules for Hybrid Flow Shop Scheduling with Parallel Batching Machines. International Journal of Production Research, 52, 3842-3857.
94. Angus Kenny, X. L., Andreas T. Ernst, Dhananjay Thiruvady, 2017. Towards Solving Large-Scale Precedence Constrained Production Scheduling Problems in Mining. Gecco, 1137-1144.
95. Anja Feldmann, J. S., Shang-Hua Teng 1994. Dynamic Scheduling on Parallel Machines. Theoretical Computer Science 130, 24.
96. Arezoo Atighehchian, M. M. S. 2013. An Environment-Driven, Function-Based Approach to Dynamic Single-Machine Scheduling. European J. Industrial Engineering, , Vol. 7, 19.
97. Atif Shahzad, N. M. 2016. Learning Dispatching Rules for Scheduling: a Synergistic View Comprising Decision Trees, Tabu Search and Simulation. Computers, 5, 3.
98. Balicki, J. 2007. Tabu Programming for Multiobjective Optimization Problems. Ijcsns International Journal of Computer Science and Network Security Vol.7
99. Banu Çaliş , S. B. 2013. A Research Survey: Review of Ai Solution Strategies of Job Shop Scheduling Problem. Journal of Intelligent Manufacturing, 26, 961-973.
100. Barták, R. 1999. Dynamic Constraint Models for Planning and Scheduling Problems. Grant Agency
101. Bing-Hai Zhou, X. L., Richard. Y. K.Fung 2013. Dynamic Scheduling of Photolithography Process Based on Kohonen Neural Network. Journal of Intelligent Manufacturing, 26, 73-85.
102. Binodini Tripathy, S. D., Sasmita Kumari Padhy, 2015. Dynamic Task Scheduling using a Directed Neural Network. Journal of Parallel and Distributed Computing, 75, 101-106.
103. Brucker, P. 2007. Scheduling Algorithms, Verlag Berlin Heidelberg Springer.
104. Byung Jun Joo, P. X. 2015. A Production Scheduling Problem with Uncertain Sequence-Dependent Set-Up Times and Random Yield. International Journal of Production Research, 53, 2820-2835.
105. C. S. Sung , J. T. R. 1987. A Dynamic Production Scheduling Model with Lost-Sales or Backlogging. Comput. opns Res., 14, 8.
106. C. S.Wong, F. T. S. C., S. H. Chung, 2013. A Joint Production Scheduling Approach Considering Multiple Resources And Preventive Maintenance Tasks. International Journal of Production Research, 51, 883-896.
107. Chao Lu, L. G., Xinyu Li, Quanke Pan,Qi Wang, 2017a. Energy-Efficient Permutation flow Shop Scheduling Problem using A Hybrid Multi-Objective Backtracking Search Algorithm. Journal Of Cleaner Production, 144, 228-238.
108. Chao Lu, L. G., Xinyu Li, Shengqiang Xiao, 2017b. A Hybrid Multi-Objective Grey Wolf Optimizer for Dynamic Scheduling in a Real-World Welding Industry. Engineering Applications of Artificial Intelligence, 57, 61-79.
109. Christoph W. Pickardt, T. H., Jurgen Branke, Jens Heger, Bernd Scholz-Reiter, 2013. Evolutionary Generation of Dispatching Rule Sets for Complex

Dynamic Scheduling Problems. International Journal of Production Economics, 145, 67-77.
110. Chuanli Zhao, F. J., T. C. E. Cheng, Min Ji, 2017. A Note on the Time Complexity Of Machine Scheduling with Dejong's Learning Effect. Computers & Industrial Engineering, 112, 447-449.
111. Chuanyu Zhao, J. F., Qiang Xu 2013. Real-Time Dynamic Hoist Scheduling For Multistage Material Handling Process under Uncertainties. Aiche Journal, 59, 465-482.
112. Cyrille Pach, T. B., Therese Bonte, Damien Trentesaux, 2014. Orca-Fms: A Dynamic Architecture for the Optimized And Reactive Control of Flexible Manufacturing Scheduling. Computers In Industry, 65, 706-720.
113. Daria Terekhov, J. C. B., Tony T. Tran 2010. Integrating Scheduling and Queueing for Dynamic Scheduling Problems.
114. Daria Terekhova, D. G. D. A. J. C. B. 2014. Queueing-Theoretic Approaches for Dynamic Scheduling: A Survey.
115. Djamila Ouelhadj, S. P. 2008. A Survey of Dynamic Scheduling In Manufacturing Systems. Journal of Scheduling, 12, 417-431.
116. Dongjuan, X. 2010. A Dynamic Scheduling Model Oriented to Flexible Production. Ieee International Coriference on Educational and Network Technology.
117. Dongni Li, Y. W., Guangxue Xiao, Jiafu Tang 2013. Dynamic Parts Scheduling in Multiple Job Shop Cells Considering Intercell Moves and Flexible Routes. Computers & Operations Research, 40, 1207-1223.
118. Edna Barbosa Da Silva, M. G. C., Marilda F´Atima De Souza Da Silva, Fabio Henrique Pereira 2014. Simulation Study of Dispatching Rules in Stochastic Job Shop Dynamic Scheduling. World Journal of Modelling and Simulation, .Vol. 10 11.
119. Eliana María González-Neira, A. R. M.-T., David Barrera, 2017. flow-Shop Scheduling Problem under Uncertainties: Review and Trends. International Journal of Industrial Engineering Computations, 399-426.
120. Florian T. Hecker, M. S., Thomas Becker, Bernd Hitzmann, 2014. Application of A Modified Ga, Aco And A Random Search Procedure to Solve the Production Scheduling of a Case Study Bakery. Expert Systems With Applications, 41, 5882-5891.
121. Gabriela N. Maschiettoa , Y. O., Martin G. Ravetti, Mauricio C. De Souza ,Farouk Yalaouib 2016. Crane Scheduling Problem With Non-Interference Constraints in a Steel Coil Distribution Center. International Journal Of Production Research.
122. Gomes, S. R. P. 2014. Selection Constructive Based Hyper-Heuristic for Dynamic Scheduling. Master Degree.
123. Heger, J., Branke, Jurgen, Hildebrandt, Torsten, Scholz-Reiter, Bernd. 2016. Dynamic Adjustment of Dispatching Rule Parameters in flow Shops with Sequence Dependent Setup Times. International Journal of Production Research.
124. Herrmann, J. W. 2006. Handbook of Production Scheduling University of Maryland, College Park, Sprineger.
125. I. Pereira , A. M. 2013. Self-Optimization Module for Scheduling using Case-Based Reasoning.
126. Ihsan Sabuncuoglu , B. G. 1996. A Neural Network Model for Scheduling Problems. European Journal of Operational Research 93, 12.
127. J.Behnamian, S. M. T. F. G. 2014. A Survey of Multi-Factory Scheduling. Journal of Intelligent Manufacturing, 27, 231-249.
128. Jiewu Leng, P. J. 2017. Dynamic Scheduling in Rfid-Driven Discrete Manufacturing System by using Multi-Layer Network Metrics As Heuristic Information. Journal of Intelligent Manufacturing.
129. Joseph Y-T. Leung"Sanjoy Baruah, J. G. 2004. Handbook of Scheduling. Scheduling Real-Time Tasks: Algorithms and Complexity, Usa, Crc Press Llc.
130. Jun Zhao, W., Kan Sun, Ying Liu 2014. A Bayesian Networks Structure Learning and Reasoning-Based Byproduct Gas Scheduling In Steel Industry. Ieee Transactions on Automation Science and Engineering, Vol. 11,.
131. Jurgen Branke, S. N., Christoph Pickardt, Mengjie Zhang, 2016. Automated Design of Production Scheduling Heuristics: A Review. Ieee Transactions on Evolutionary Computation, 20, 110-124.
132. Jurgenbranke , S. N., Christoph Pickardt , Mengjie Zhang 2016. Automated Design of Production Scheduling Heuristics: A Review. Ieee Transactions on Evolutionary Computation, 20, 110-124.
133. Kaban, A. K., Othman, Z, Rohmah, D. S. 2012. Comparison of Dispatching Rules in Job-Shop Scheduling Problem using Simulation: a Case Study. Int J Simul Model (2012), 11, 12.
134. Kalinowski Krzysztof , K. D., Grabowik Cezary 2013. Predictive - Reactive Strategy for Real Time Scheduling of Manufacturing Systems. Applied Mechanics and Materials, 307, 470-473.
135. Kaminsky, P. 2006. Models and Algorithms for Integratedmulti - Stage Production/Distribution Systems: Third Party Logistics. Nsf Design, Service, Andmanufacturing Grantees and Research Conference, St. Louis,Missouri Grant #Dmi - 0200439.
136. Kumar, V. S., O.J. , Soni, G. , Kumar, R. 2014. A Review on Artificial Neural Network Approach in Manufacturing Systems. Https://Www.Researchgate.Net/Publication/273695480.
137. Lei Wang, J. C., Ming Li, Zhihu Liu, 2017. Flexible Job Shop Scheduling Problem using an Improved

Ant Colony Optimization. Scientific Programming, 2017, 1-11.
138. Li, Y. & Chen, Y. 2010. A Genetic Algorithm For Job-Shop Scheduling. Journal of Software, 5.
139. Li Yuqing , W. R., Xu Minqiang 2014. Rescheduling of Observing Spacecraft using Fuzzy Neural Network and Ant Colony Algorithm. Chinese Journal of Aeronautics, 27, 678-687.
140. Liping Zhang, X. L., Liang Gao, Guohui Zhang, 2013. Dynamic Rescheduling in Fms that is Simultaneously Considering Energy Consumption And Schedule Efficiency. the International Journal of Advanced Manufacturing Technology, 87, 1387-1399.
141. Lixin Tang , W. L., J I Y I N Li U, 2005. A Neural Network Model and Algorithm for The Hybrid Flow Shop Scheduling Problem in a Dynamic Environment. Journal Of Intelligent Manufacturing, 16, 361–370, 2005.
142. M. A.Adibi, M. Z., M.Amiri 2010. Multi-Objective Scheduling of Dynamic Job Shop using Variable Neighborhood Search. Expert Systems with Applications, 37, 282-287.
143. Mehdi Abedi, H. S., Hamed Fazlollahtabar 2017. Hybrid Scheduling and Maintenance Problem Using Artificial Neural Network Based Meta-Heuristics. Journal of Modelling In Management, 00-00.
144. Omara, F. A. & Arafa, M. M. 2010. Genetic Algorithms for Task Scheduling Problem. Journal of Parallel and Distributed Computing, 70, 13-22.
145. Ouelhadj D., P. S. 2009. Survey of Dynamic Scheduling in Manufacturing Systems. Journal of Scheduling, 12., 27.
146. Paolo Priore, D. D. L. F., Raúl Pino, Javier Puente 2001. Dynamic Scheduling of Flexible Manufacturing Systems using Neural Networks and Inductive Learning.
147. Paolo Priore, R. P., Jose Parreño, Javier Puente, Borja Ponte 2015. Real-Time Scheduling of Flexible Manufacturing Systems using Support Vector Machines And Case-Based Reasoning. Journal of Economics, Business and Management,, Vol. 3
148. Rakesh Kumar, M. A., Haryana 2016. Multi Agents Approach for Job Shop Scheduling Problem using Genetic Algorithm and Variable Neighborhood Search Method. The 20th World Multi-Conference on Systemics, Cybernetics and Informatics Wmsci.
149. Sahana, S. K., Jain, A. & Mahanti, P. K. 2014. Ant Colony Optimization for Train Scheduling: an Analysis. International Journal of Intelligent Systems and Applications, 6, 29-36.
150. Sana Alyaseri, K. R. K.-M. 2013. Multi Objective Bee Colony Optimization Framework for Grid Job Scheduling. the 4th International Conference on Computing and Informatics (Http://Www.Uum. Edu.My).
151. T. Eguchi, F. O., T. Hirai 1999. A Neural Network Approach To Dynamic Job Shop Scheduling. K. Mertins Et Al. (Eds.), Global Production Management.
152. Tarun Kanti Jana, B. B., Soumen Paul, Bijan Sarkar, Jyotirmoy Saha 2013. Dynamic Schedule Execution In an Agent Based Holonic Manufacturing System. Journal of Manufacturing Systems, 32, 801-816.
153. Tarun Kanti Jana, B. B., Soumen Paul, Bijan Sarkar, Jyotirmoy Saha, 2013. Dynamic Schedule Execution in an Agent Based Holonic Manufacturing System. Journal of Manufacturing Systems, 32, 801-816.
154. Tubilla, F. 2011. Dynamic Scheduling of Manufacturing Systems With Setups And Random Disruptions. Phd Thesis, Massachusetts Institute of Technology.
155. Yiping Wen, J. L., Zhigang Chen, Buqing Cao 2014. Dynamic Scheduling Optimization for Instance Aspect Handling In Workflows.
156. Yuxin Zhai , K. B., Fu Zhao,John W. Sutherland 2017. Dynamic Scheduling of A flow Shop with on-Site Wind Generation for Energy Cost Reduction under Real Time Electricity Pricing. Cirp Annals - Manufacturing Technology, 66, 41-44.
157. Zaki Ahmad Khan, J. S., Mahfooz Alam, 2017. Dynamic Scheduling Algorithm for Variants Of Hypercube Interconnection Networks. Indian Journal of Science and Technology, 10, 1-5.
158. Zhicheng Cai, X. L., Ruben Ruiz, Qianmu Li 2017. A Delay-Based Dynamic Scheduling Algorithm for Bag-Of-Task Workflows with Stochastic Task Execution Times in Clouds. Future Generation Computer Systems, 71, 57-72.