Artificial Intelligence formulated this projection for compatibility purposes from the original article published at Global Journals. However, this technology is currently in beta. *Therefore, kindly ignore odd layouts, missed formulae, text, tables, or figures.* 

# A Review for Dynamic Scheduling in Manufacturing

Khalid Muhamadin Mohamed Ahmed Bukkur<sup>1</sup>, M.I. Shukri<sup>2</sup> and Osama Mohammed Elmardi<sup>3</sup>
 <sup>1</sup> Nile Valley University

Received: 9 December 2017 Accepted: 4 January 2018 Published: 15 January 2018

#### 7 Abstract

1

5

This paper discusses review of literature of dynamic scheduling in manufacturing. First, the 8 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 10 open shop. A variety of approaches have been developed to solve the problem of dynamic 11 scheduling. Dynamic scheduling could be classified into four categories, completely reactive 12 scheduling, predictive-reactive scheduling, robust predictive reactive scheduling, and robust 13 proactive scheduling. It is better to combine together different techniques such as operational 14 research and artificial intelligence to overcome dynamic scheduling problems so as to endow 15 the scheduling system with the required flexibility and robustness, and to suggest various 16 orientations for further work is this area of research. 17

18

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

23 was solved and determined the best ways for dealing with this problem.

#### <sup>24</sup> 1 a) Definition of dynamic scheduling problems

A dynamic scheduling problem is generally viewed as a collection of linked static problems. Scheduling in 25 manufacturing is an activity of allocating jobs to resources with respect to a time frame that considers critical 26 ratio and considered as N-P hard type of problem (Tarun Kanti Jana, 2013). The main problem in job-shop 27 and flexible job-shop scheduling is that of obtaining the best possible schedules with optimal solutions (Ahmad 28 Shahrizal Muhamad, 2011). There is a need to incorporate these dynamic events into the scheduling process, in 29 order to ensure feasibility of the scheduling plan that the manufacturing system is following. Realtime scheduling 30 theory has traditionally focused upon the development of algorithms for feasibility analysis (determining whether 31 all jobs can complete execution by their deadlines) and run-time scheduling (generating schedules at run-time 32 for systems that are deemed to be feasible) of such systems (Joseph Y-T. Leung"Sanjoy Baruah 2004). The 33 problem of scheduling in the presence of real time events, termed dynamic scheduling. Real-time events have 34 been classified into two categories. 35

#### <sup>36</sup> 2 b) Scheduling problem classifications

<sup>37</sup> Suppose that (m) machines ( )m j M j

38 ,..., 1 = have to process (n) jobs ()

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

<sup>42</sup> processing time, etc. (Djamila . Also (A. S. , and (Chao Lu, 2017b) agree with that categories.

<sup>19</sup> Index terms— dynamic scheduling, rescheduling, real-time events, operational research, artificial intelli-20 gence.

43 ynamic scheduling is the process of absorbing the effect of real-time events, analyzing the current status of

44 scheduling and automatically modifying the schedule with optimized measures in order to mitigate disruptions 45 (Amer Fahmya, 2014). Also dynamic scheduling which is named rescheduling and it is the process of updating

46 an existing production schedule in response to disruptions or other change . Also dynamic scheduling is a

47 direct allocation of tasks to resources, according to given sequencing rules (Kalinowski Krzyszt of 2013). Real-

48 world scheduling problems are combinatorial, dynamic and stochastic (Daria . The goal in such problems is to

49 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. . 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

 $_{54}$  about are characterized by a stream of products that should D one or more machines . The scheduling problems

<sup>55</sup> are classified based on the nature of the shop configuration into five classes, i.e., single machine, parallel machines,

<sup>56</sup> flow shop, job shop, and open shop(J.Behnamian 2014)(Eliana María González-Neira, 2017).

#### <sup>57</sup> 3 c) Optimality criteria (objective functions)

 $_{\rm 58}$   $\,$  We denote the finishing time of job i J by i C , and the associated cost by ( )i i C f

max : tardiness i i d C D ? = : absolute deviation ()2

i : i i i d C S ? = squared deviation i i i d ifC U ? = 0 : , 1 otherwise unit penalty.

#### <sup>63</sup> 4 With each of these functions

64 ? ? i i i i i i G w G G w G , , max , max , i T ? , i i T w ? , i U ? , i i U w ? , i D ? , i i D w ? , i S ? , i i S w ? , 65 i E ? i i E w

 $_{66}$  . Linear combinations of these objective functions are also considered. An objective function which is non  $_{67}$  decreasing with respect to all variables i C is called regular. Functions involving i i S D E , ,

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

70 (operation) can be processed earlier without changing the processing order or violating the constraints .

# <sup>71</sup> 5 Global Journal of Researches in Engineering () Volume XVIII <sup>72</sup> Issue V Version I

<sup>73</sup> Practical experience shows that some computational problems are easier to solve than others. Complexity theory <sup>74</sup> provides a mathematical framework in which computational problems are studied so that they can be classified <sup>75</sup> as "easy" or "hard". One of the main issues of complexity theory is to measure the performance of algorithms <sup>76</sup> with respect to computational time. A problem is called polynomially ()P solvable if there exists a polynomial <sup>77</sup> p such that ()()() x p O x T ?

for all inputs x for the problem, i.e. if there is a k such that () () k x O x T? (Jun Zhao, 2014).

79 A commonly faced problem in flow-shop scheduling is that it belongs to the class of NP-hard problems (Florian

T. . 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 NPcomplete (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

<sup>85</sup> 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.

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 i f are not specified, we set ?= max f or ?= ?

if. However, in most cases we consider special functions if. The most common objective functions are that
 make span max Other objective functions depend on due dates i d which are associated with jobs i J. We define

95 for each job i J :{ i C | n i ,..., 1 =},

#### 96 6 III. CURRENT DYNAMIC SCHEDULING APPROACHES

97 Dynamic scheduling divided into four categories, completely reactive scheduling, predictivereactive scheduling, 98 robust predictive-reactive scheduling, and robust pro-active scheduling. In (Amer Fahmya, 2014) and (Djamila <sup>99</sup> there are three main dynamic scheduling categories (or strategies),completely reactive scheduling, robust pro-<sup>100</sup> active scheduling, predictive-reactive scheduling.

# <sup>101</sup> 7 a) Completely reactive scheduling

In completely reactive scheduling no firm schedule is generated in advance and decisions are made locally in 102 real-time. A dispatching rule is used to select the next job with highest priority to be processed from a set of 103 jobs awaiting service at a machine that becomes free. This scheduling type termed as "Dispatching" or "Priority 104 Rule-based Scheduling". This approach was introduced by (Dongjuan, 2010) who proposed a dynamic scheduling 105 established through an aloging connectivity. A new policy proposed for scheduling systems with setups, the 106 Hedging Zone Policy (HZP) policy belongs to what we called the Clearing Cruising (CC) Class, which includes 107 all produce-up-to or base stock policies. There was another work presented deal with dynamic task allocation 108 mechanism for machine scheduling in a job shop environment following agent based holonic control approach. 109 (Tarun Kanti Jana 2013). A new optimization-based control algorithm was proposed that developed for the 110 buffer management and the production scheduling of a multiple-line production plant (Andrea Cataldo 2015). 111 An approach to dynamically adjust the parameters of a dispatching rule was presented depending on the current 112 system conditions by using machine learning method and demonstrate the capability of their work by reducing 113 the mean tardiness of job. There was another article deals with a parallel machine scheduling problem subject 114 to non-interference constraints. The good results presented by the heuristic enable the evaluation of different 115 storage policies for real size instances (Gabriela N. Maschiettoa 2016). A work of a multi-agent-based dynamic 116 scheduling system was introduce for manufacturing flow lines (MFLs) using the Prometheus methodology (PM) 117 considering the dynamic customer demands and internal disturbances. The proposed decision making system 118 supports both static and dynamic scheduling (Ali Vatankhah Barenji, 2016). A complex manufacturing network 119 model CMNBS was proposed for RFID "radio frequency identification" -driven DMS" discrete manufacturing 120 system" modeling, performance analyzing and dynamic scheduling (Jiewu Leng, 2017). 121

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).

#### <sup>127</sup> 8 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). 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).

#### <sup>134</sup> 9 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.

#### <sup>137</sup> 10 e) Comparison of dynamic scheduling approaches

Dynamic scheduling has been defined under four categories: on-line scheduling (completely reactive approaches), 138 predictive-reactive scheduling, robust predictive-reactive scheduling, and robust pro-active scheduling. 139 In completely reactive scheduling, schedules are easily generated using dispatching rules. However, the solution 140 quality is poor due to the nature of these rules. Predictive-reactive scheduling is the most common approach 141 in dynamic scheduling. Predictive reactive approaches search in a larger solution space, generate high quality 142 schedules, and can generate better system performance to increase productivity and minimize operating costs 143 compared with on-line scheduling and predictive scheduling. Simple schedule adjustments require little effort 144 and are easy to implement. However, they may lead to poor system performance. Generating robust schedules 145 lead to better system performance, even though robustness measures are not easy to define. Predictive-reactive 146 scheduling is a scheduling/ rescheduling process in which schedules are revised in response to real-time events. 147 148 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 149 150 schedule is then modified during execution in response to real-time events .(Abdallah Introduced a new approach for solving dynamic RCPSP "Resource Constrained Project Scheduling Problem" instances. This work is based 151 on new constraint programming techniques. And provided a complete system able to handle both dynamic and 152 over-constrained scheduling problems. (Chuanyu Zhao, 2013) Proposed a novel and rigorous RDHS "real-time 153 dynamic hoist Scheduling " methodology , which takes into account uncertainties of new coming jobs and targets 154 real-time scheduling optimality and applicability. (Bing-hai Zhou, 2013) Proposed a dynamic scheduling method 155 of the photolithography process based on kohonen neural network. It determines the optimal combination of 156

scheduling policies due to the special system status. (Gomes, 2014) Stated that dynamic events must be taken 157 into account, since they may have a major impact on the schedule. They can change the system status and affect 158 performance. Manufacturing systems require immediate response to these dynamic events. (Paolo Priore, 2015) 159 Stated that dispatching rules are usually applied to schedule jobs in Flexible Manufacturing Systems (FMSs) 160 dynamically. A scheduling approach that employs Support Vector Machines (SVMs) and case-based reasoning 161 (CBR) was proposed.(Yuxin Zhai 2017) Proposed adynamic scheduling approach to minimize the electricity cost 162 of a flow shop with a grid-integrated wind turbine. (Chao Lu, 2017b)There was another work developed a 163 highperformance multi-objective predictive-reactive scheduling method for this MODWSP in order to narrow the 164 gap between theoretical research and applicable practice. 165

#### 166 11 Global

#### 167 12 DYNAMIC SCHEDULING TECHNIQUES APPLIED t O 168 MANUFACTURING SYSTEMS

#### <sup>169</sup> 13 a) Dispatching rules

Dispatching rules have played a significant role within dynamic contexts. From the literature reviewed, Dispatching heuristic was able to provide not only a good solution but also the best solutions for the system observed. 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.

#### <sup>176</sup> 14 b) Heuristics techniques

Heuristics are problem specific schedule repair methods, which do not guarantee to find an optimal schedule, but 177 178 have the ability to find reasonably good solutions in a short time. The most common schedule repair heuristics 179 are: right-shift schedule repair, match-up schedule repair, and partial schedule repair. Dispatching rules are also heuristics that have played a significant role in completely reactive scheduling. And used in real-time to select the 180 next job waiting for processing at a resource (Djamila. (JurgenBranke 2016) In this work constitutes the first 181 comprehensive review of hyper-heuristics for the automated design of production scheduling heuristics, providing 182 a simple taxonomy and focusing on key design choices such as the learning method, attributes, representation 183 and fitness evaluation. (Andrea Rossi, 2013). 184

#### <sup>185</sup> 15 c) Meta-heuristics Techniques

Meta-heuristics (tabu search, simulated annealing, the ant colony algorithm, bee colony and genetic algorithms) 186 have been successfully used to solve production scheduling problems. Meta-heuristics have been widely used 187 to solve static deterministic production scheduling. However, little research work has addressed the use of 188 metaheuristics in dynamic scheduling (Djamila . Tabu search algorithm is the alternative approaches to the 189 modern meta-heuristic optimization techniques . In this work a framework for multi objective bee colony 190 optimization is proposed to schedule batch jobs to available resources where the number of jobs is greater than the 191 number of resources (Sana Alyaseri, 2013). Ant Colony Optimization (ACO) is a meta-heuristic technique and is 192 used to find shortest path between source and destination. The ant colony algorithm is a new method to deal with 193 the rescheduling problem of observing spacecraft. In this work, an efficient an improved ant colony optimization 194 195 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 196 (GRASP) also used to solve dynamic scheduling problems (Adil Baykaso?lu, 2017). Also, a hybrid genetic and 197 simulated annealing algorithms is developed because of the high potential of outcomes to be trapped in the local 198 optima (Aidin Delgoshaei, 2016). As solution approaches, two meta-heuristic solution approaches based on the 199 simulated annealing (SA) algorithm and the discrete particle swarm optimization (DPSO) are proposed to obtain 200 a near optimal solution in a reasonable amount of time (Byung Jun Joo, 2015). There was another work proposed a 201 GA for solving the agile job shop scheduling to minimize the make span. Also in this work, an implementation of a 202 standard GA (SGA) to solve the task scheduling problem has been presented (Omara and Arafa, 2010). A genetic 203 algorithm approach is applied to hypothetical numerical examples with the objective of minimizing the makespan 204 205 in the work of (C. S. ??ong, 2013) Hyper-heuristics are defined as "an automated methodology for selecting or 206 generating heuristics to solve hard computational search problems" (Jurgen Branke, 2016). There was another 207 work developed a two-stage hyper-heuristic to automatically generate sets of dispatching rules for complex and 208 dynamic scheduling problems. The approach combines a GP hyper-heuristic that evolves a composite rule from basic attributes (Christoph W. . There was another study used a hybrid heuristic model combining both Genetic 209 Algorithm (GA) and Fuzzy Neural Network (FNN) (Alper . This work introduces a two-phase hybrid solution 210 method. The first phase relies on solving a series of linear programming problems to generate an initial solution. 211 In the second phase, a variable neighborhood descent procedure is applied to improve the solution (Amina . 212 This work presented a Greedy Randomized Adaptive Search Procedure (GRASP)-Mixed Integer Programming 213

(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).

220

# <sup>221</sup> 16 e) Artificial intelligence techniques

A number of dynamic scheduling problems have adopted artificial intelligence techniques such as knowledge-basedsystems, neural networks, casebased reasoning, fuzzy logic, Petri nets, etc. (Banu Çali? 2013). (LIXIN TANG 2005)(T. 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. To derive better dynamic scheduling systems, some researchers developed hybrid systems which combine various

227 artificial intelligence techniques (Binodini Tripathy, 2015).

#### <sup>228</sup> 17 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. In the present work, Multiagents was proposed to find the near optimal solution for job shop scheduling problem using GA and VNS approach in parallel (Rakesh .

## <sup>233</sup> 18 g) The model of network topology technique

A contribution made towards solving the problem of dynamic scheduling on parallel machines by introducing a

<sup>235</sup> model of network topology technique which captures some important aspects of the practical scheduling problem

236 (Anja Feldmann 1994).

## <sup>237</sup> 19 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 .

# <sup>241</sup> 20 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).

# <sup>247</sup> 21 j) Comparison of dynamic scheduling techniques

In order to ascertain the value of the various solution techniques, there has been some published work comparing 248 249 some of these techniques. Heuristics have been widely used to react to the presence of realtime events because 250 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 251 been provided in the literature to compare the performance of tabu search, genetic algorithms, and simulated 252 annealing. Unlike simulated annealing and tabu search based on manipulating one feasible solution, genetic 253 algorithms manipulate a population of feasible solutions. Genetic algorithms were found not efficient to find 254 a nearoptimal solution in a reasonable time compared to tabu search and simulated annealing which operate 255 on a single configuration and not on an entire population. Knowledge-based systems possess the potential for 256 automating human expert reasoning and heuristic knowledge to run production scheduling systems. In terms of 257 effectiveness of the decision-making capability, knowledge-based systems are limited by the quality and integrity 258 of the specific domain knowledge. Fuzzy logic has not yet been explored to its fullest potential. Neural networks 259 260 cannot guarantee to provide optimal decisions, but their learning capability makes them to have a lot of promise. 261 In addition, in developing practical integrated dynamic scheduling systems, it is necessary to combine together 262 different techniques such as operational research and artificial intelligence to endow the scheduling system with 263 the required flexibility and robustness (Djamila . 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 264 heuristics with more sophisticated (global) solution algorithms as well as between different hyper-heuristics are 265 needed. So far, such comparisons have been rather limited hyper-heuristic approaches have strengths compared 266 to global optimization approaches in particular in dynamic and stochastic environments where a quick reaction 267 is important. They also become more competitive as the problem size (and thus the search space for the 268

global optimizer) increases. One reason for the limited number of comparisons may be that hyper-heuristics 269 possess several properties that make a fair comparison particularly difficult. For example, not only are the 270 hyper-heuristics stochastic algorithms with many parameters to tune, but also is the evaluation function often a 271 272 stochastic simulation, resulting in stochastic fitness values. Also, the running time for the simulations can be quite 273 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 274 rule itself. This implies that a comparison of hyper heuristics based on the same number of function evaluations 275 has limited validity (Jurgen Branke, 2016). For The network topology technique there was a question which 276 remain open were, how can the model be extended to capture the practical scheduling even better? and if the 277 competitive ratio is the right performance measurement? also of interest is whether randomization can help to 278 improve the performance of the scheduling algorithm (Anja Feldmann 1994). About constraints programming 279 despite of studying the proposed framework using the complex process environment background we believe 280 that the results are applicable in general to other (non-production) problem areas where mixed planning and 281 scheduling capabilities are desirable. The efficiency of the function based approach is evaluated against the most 282 commonly used dispatching rules. Moreover, the proposed approach is compared with an agent-based approach, 283 which employs the Q-learning algorithm to develop a decision-making policy. Experimental results show that the 284 285 proposed approach is an effective method for dynamic single-machine scheduling (Arezoo Atighehchian 2013).

286 A dynamic scheduling is not dissection making problem but it is optimization problem. And it concerns 287 with resources available, the jobs that should be done and the perfect time to do jobs. In manufacturing 288 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 289 events for allocating jobs to resources in manufacturing. From the above we can define dynamic scheduling 290 like this "A dynamic scheduling is the optimum Utilization between resources and jobs in real time events". 291 Predictive-reactive scheduling is the most common approach in doing dynamic scheduling. It searches in a 292 larger solution space, generate high quality schedules, and can generate better system performance to increase 293 productivity and minimize operating costs compared with on-line scheduling and predictive scheduling. In 294 computational complexity sense optimization problems belongs to the class of NP-hard problems. Not all NP-295 hard problems are equally hard from a practical perspective. We have seen that some NP-hard problems can 296 be solved pseudopolynomially using dynamic programming or "hill climbing", known as local (or neighborhood) 297 search Dynamic scheduling has been solved using many techniques. It is necessary to combine together different 298 techniques such as operational research and artificial intelligence to endow the scheduling system with the required 299 flexibility and robustness for example integrating neural networks, simulation, and expert systems or a hybrid 300 approach. I think that dynamic scheduling has a main role in developing the fourth industrial revolution. 301

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 NPhard 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 La destare 4.0% the fourth is destared and the property of the set of the set

1309 Industry 4.0"the fourth industrial revolution", and as a core element of systems engineering, also doing

 $<sup>^{1}</sup>$ © 2018 Global Journals



Figure 1: iG



Figure 2: .



Figure 3: Figure 1 :

- 310 [Computers Industrial Engineering], Computers & Industrial Engineering 112 p. .
- 311 [Computers Industrial Engineering], Computers & Industrial Engineering 112 p. .
- 312 [Brucker ()], P Brucker. 2007. Berlin Heidelberg Springer.
- 313 [Brucker ()], P Brucker. 2007. Berlin Heidelberg Springer.
- [Amer Fahmya and Bassionic ()], T M H Amer Fahmya, Hesham Bassionic. Pm World Journal 2014. 9.
- $_{\tt 315}~[{\rm Barbosa}~{\rm Da}$ et al. ()] , Edna Barbosa Da , M ${\rm G}~{\rm C}$ Silva , Marilda F´atima De Souza Da , Fabio Henrique Silva
- , Pereira . Simulation Study of Dispatching Rules In Stochastic Job Shop Dynamic Scheduling. World Journal
   of Modelling and Simulation 2014. 10 p. 11.
- [Kumar et al. ()], V S Kumar, O J Soni, G Kumar, R. Https://Www.Researchgate.Net/Publication/
   273695480 a Review on Artificial Neural Network Approach in Manufacturing Systems 2014.
- [Amer Fahmya and Bassionic ()], T M H Amer Fahmya, Hesham Bassionic. Pm World Journal 2014. 9.
- [Zhao et al. ()] 'A Bayesian Networks Structure Learning and Reasoning-Based Byproduct Gas Scheduling in
   Steel Industry'. Jun Zhao , W Kan Sun , Ying Liu . *Ieee Transactions on Automation Science and Engineering* 2014. 11.
- [Zhao et al. ()] 'A Bayesian Networks Structure Learning and Reasoning-Based Byproduct Gas Scheduling In
   Steel Industry'. Jun Zhao , W Kan Sun , Ying Liu . *Ieee Transactions on Automation Science and Engineering*
- 2014. 11.
- [Cai et al. ()] 'A Delay-Based Dynamic Scheduling Algorithm for Bag-of-Task Workflows With Stochastic Task
   Execution Times in Clouds'. Zhicheng Cai , XL , Ruben Ruiz , Qianmu Li . Future Generation Computer
   Systems 2017. 71 p. .
- [Cai et al. ()] 'A Delay-Based Dynamic Scheduling Algorithm for Bag-Of-Task Workflows with Stochastic Task
   Execution Times in Clouds'. Zhicheng Cai , XL , Ruben Ruiz , Qianmu Li . Future Generation Computer
   Systems 2017. 71 p. .
- 333 [Vatankhah Barenji et al. ()] 'A Dynamic Multi-Agent-Based Scheduling Approach for Smes'. Ali Vatankhah
- Barenji , RV B , Danial Roudi , Majid Hashemipour . The International Journal of Advanced Manufacturing
   Technology 2016. 89 p. .
- [Vatankhah Barenji et al. ()] 'A Dynamic Multi-Agent-Based Scheduling Approach for Smes. the'. Ali Vatankhah
   Barenji , RV B , Danial Roudi , Majid Hashemipour . International Journal of Advanced Manufacturing
   Technology 2016. 89 p. .
- [Sung ()] 'A Dynamic Production Scheduling Model With Lost-Sales or Backlogging'. C S Sung , JT R . Comput.
   Opns Res 1987. 14.
- [Sung ()] 'A Dynamic Production Scheduling Model with Lost-Sales or Backlogging'. C S Sung , JT R . Comput.
   opns Res 1987. 14.
- [Dongjuan ()] 'A Dynamic Scheduling Model Oriented to Flexible Production'. X Dongjuan . Ieee International
   *Coriference on Educational and Network Technology* 2010.
- [Dongjuan ()] 'A Dynamic Scheduling Model Oriented to Flexible Production'. X Dongjuan . Ieee International
   *Coriference on Educational and Network Technology* 2010.
- <sup>347</sup> [Li and Chen ()] 'A Genetic Algorithm for Job-Shop Scheduling'. Y Li , Y Chen . Journal of Software 2010. 5.
- 348 [Li and Chen ()] 'A Genetic Algorithm For Job-Shop Scheduling'. Y Li, Y Chen. Journal of Software 2010. 5.
- [Lamghari ()] 'A Hybrid Method Based on Linear Programming And Variable Neighborhood Descent for
   Scheduling Production in Open-Pit Mines'. Amina Lamghari , RD J A F . Journal of Global Optimization
- Scheduling Production in Open-Pit Mines'. Amina Lamghari , RD J A F . Journal of Global Optimization
   2014. 63 p. .
- ILamghari ()] 'A Hybrid Method Based On Linear Programming and Variable Neighborhood Descent for
   Scheduling Production in Open-Pit Mines'. Amina Lamghari , RD J A F . Journal of Global Optimization
   2014. 63 p. .
- [Lu et al. ()] 'A Hybrid Multi-Objective Grey Wolf Optimizer for Dynamic Scheduling in a Real-World Welding
   Industry'. Chao Lu , LG , Xinyu Li , Shengqiang Xiao . Engineering Applications of Artificial Intelligence
   2017b. 57 p. .
- [Lu et al. ()] 'A Hybrid Multi-Objective Grey Wolf Optimizer for Dynamic Scheduling in a Real-World Welding
   Industry'. Chao Lu , LG , Xinyu Li , Shengqiang Xiao . Engineering Applications of Artificial Intelligence
   2017b. 57 p. .
- <sup>361</sup> [Wong and Chung ()] 'A Joint Production Scheduling Approach Considering Multiple Resources and Preventive
- Maintenance Tasks'. C S Wong , FT S C , S H Chung . International Journal of Production Research 2013. 51 p. .
- 363 51 p. .

#### 21 J) COMPARISON OF DYNAMIC SCHEDULING TECHNIQUES

- <sup>364</sup> [Wong and Chung ()] 'A Joint Production Scheduling Approach Considering Multiple Resources And Preventive
- Maintenance Tasks'. C S Wong , FT S C , S H Chung . International Journal of Production Research 2013. 51 p. .
- <sup>367</sup> [Delgoshaei ()] 'A Multi-Period Scheduling of Dynamic Cellular Manufacturing Systems in the Presence of Cost
   <sup>368</sup> Uncertainty'. Aidin Delgoshaei , AA . Computers & Industrial Engineering 2016. 100 p. . (Mohd Khairol
- 369 Anuar Ariffin, Chandima Gomes)
- 370 [Delgoshaei ()] 'A Multi-Period Scheduling of Dynamic Cellular Manufacturing Systems in the Presence of Cost
- Uncertainty'. Aidin Delgoshaei , AA . Computers & Industrial Engineering 2016. 100 p. . (Mohd Khairol
   Anuar Ariffin, Chandima Gomes)
- [Eguchi and Hirai (ed.) ()] A Neural Network Approach To Dynamic, T Eguchi , FO , T Hirai . Job Shop
   Scheduling. K. Mertins Et Al. (ed.) 1999. Global Production Management.
- [Eguchi and Hirai (ed.) ()] A Neural Network Approach To Dynamic, T Eguchi , FO , T Hirai . Job Shop
   Scheduling. K. Mertins Et Al. (ed.) 1999. Global Production Management.
- [Tang and Li ()] 'A Neural Network Model And Algorithm for the Hybrid Flow Shop Scheduling Problem in a
   Dynamic Environment'. Lixin Tang , WL , J I Y I N Li , U . Journal of Intelligent Manufacturing 2005. 2005.
- 16 p. .
- [Tang and Li ()] 'A Neural Network Model and Algorithm for The Hybrid Flow Shop Scheduling Problem in a
   Dynamic Environment'. Lixin Tang , WL , J I Y I N Li , U . Journal Of Intelligent Manufacturing 2005.
   2005. 16 p. .
- <sup>383</sup> [Ihsan Sabuncuoglu ()] 'A Neural Network Model For Scheduling Problems'. B G Ihsan Sabuncuoglu . European
   <sup>384</sup> Journal of Operational Research 1996. 93 p. 12.
- [Ihsan Sabuncuoglu ()] 'A Neural Network Model for Scheduling Problems'. B G Ihsan Sabuncuoglu . European
   Journal of Operational Research 1996. 93 p. 12.
- [Seker and Botsali ()] 'A Neuro-Fuzzy Model for A New Hybrid Integrated Process Planning and Scheduling
   System'. Alper Seker , SE , Reha Botsali . *Expert Systems with Applications* 2013. 40 p. .
- [Seker and Botsali ()] 'A Neuro-Fuzzy Model for A New Hybrid Integrated Process Planning and Scheduling
   System'. Alper Seker , SE , Reha Botsali . *Expert Systems with Applications* 2013. 40 p. .
- [Zhao et al. ()] A Note on the Time Complexity of Machine Scheduling with Dejong's Learning Effect, Chuanli
   Zhao, FJ, T C E Cheng, Min Ji. 2017.
- [Zhao et al. ()] A Note on the Time Complexity Of Machine Scheduling with Dejong's Learning Effect, Chuanli
   Zhao, FJ, T C E Cheng, Min Ji. 2017.
- Byung Jun Joo ()] 'A Production Scheduling Problem with Uncertain Sequence-Dependent Set-Up Times and
   Random Yield'. P X Byung Jun Joo . International Journal of Production Research 2015. 53 p. .
- <sup>397</sup> [Byung Jun Joo ()] 'A Production Scheduling Problem with Uncertain Sequence-Dependent Set-Up Times and
   <sup>398</sup> Random Yield'. P X Byung Jun Joo . International Journal of Production Research 2015. 53 p. .
- Banu Çali? ()] 'A Research Survey: Review of Ai Solution Strategies of Job Shop Scheduling Problem'. S B
   Banu Çali? . Journal of Intelligent Manufacturing 2013. 26 p. .
- [Banu Çali? ()] 'A Research Survey: Review of Ai Solution Strategies of Job Shop Scheduling Problem'. S B
   Banu Çali? . Journal of Intelligent Manufacturing 2013. 26 p. .
- [Kumar et al. ()] A Review on Artificial Neural Network Approach in Manufacturing Systems, V S Kumar , O J
   Soni , G Kumar , R . Https://Www.Researchgate.Net/Publication/273695480 2014.
- [Ouelhadj ()] 'A Survey of Dynamic Scheduling In Manufacturing Systems'. Djamila Ouelhadj , SP . Journal of
   Scheduling 2008. 12 p. .
- 407 [Ouelhadj ()] 'A Survey of Dynamic Scheduling In Manufacturing Systems'. Djamila Ouelhadj , SP . Journal of
   408 Scheduling 2008. 12 p. .
- <sup>409</sup> [Behnamian ()] 'A Survey of Multi-Factory Scheduling'. J Behnamian , SM T F G . Journal of Intelligent
   <sup>410</sup> Manufacturing 2014. 27 p. .
- <sup>411</sup> [Behnamian ()] 'A Survey of Multi-Factory Scheduling'. J Behnamian , SM T F G . Journal of Intelligent
   <sup>412</sup> Manufacturing 2014. 27 p. .
- [Santos et al. ()] Alternative Approaches Analysis for Scheduling in an Extended Manufacturing Environment, A
   S Santos , ML R V , G D A M Putnik , Madureira . 2014. Ieee.
- [Santos et al. ()] Alternative Approaches Analysis for Scheduling in an Extended Manufacturing Environment, A
   S Santos , ML R V , G D A M Putnik , Madureira . 2014. Ieee.
- <sup>417</sup> [Shahrizal Muhamad ()] 'An Artificial Immune System for Solving Production Scheduling Problems: A Review'.
  <sup>418</sup> Ahmad Shahrizal Muhamad , SD . Artificial Intelligence Review 2011. 39 p. .

- <sup>419</sup> [Shahrizal Muhamad ()] 'An Artificial Immune System for Solving Production Scheduling Problems: A Review'.
   <sup>420</sup> Ahmad Shahrizal Muhamad , SD . Artificial Intelligence Review 2011. 39 p. .
- <sup>421</sup> [Arezoo Atighehchian ()] 'An Environment-Driven, Function-Based Approach to Dynamic Single-Machine
   <sup>422</sup> Scheduling'. M M S Arezoo Atighehchian . *European J. Industrial Engineering* 2013. 7 p. 19.
- <sup>423</sup> [Arezoo Atighehchian ()] 'An Environment-Driven, Function-Based Approach to Dynamic Single-Machine
   <sup>424</sup> Scheduling'. M M S Arezoo Atighehchian . *European J. Industrial Engineering* 2013. 7 p. 19.
- <sup>425</sup> [Sahana et al. ()] 'Ant Colony Optimization for Train Scheduling: an Analysis'. S K Sahana , A Jain , P K
   <sup>426</sup> Mahanti . International Journal of Intelligent Systems and Applications 2014. 6 p. .
- <sup>427</sup> [Sahana et al. ()] 'Ant Colony Optimization for Train Scheduling: an Analysis'. S K Sahana , A Jain , P K
   <sup>428</sup> Mahanti . International Journal of Intelligent Systems and Applications 2014. 6 p. .
- 429 [Hecker et al. ()] 'Application of A Modified Ga, Aco and a Random Search Procedure to Solve the Production
- Scheduling of A Case Study Bakery'. Florian T Hecker, MS, Thomas Becker, Bernd Hitzmann. Expert
   Systems with Applications 2014. 41 p. .
- [Hecker et al. ()] 'Application of A Modified Ga, Aco And A Random Search Procedure to Solve the Production
  Scheduling of a Case Study Bakery'. Florian T Hecker, MS, Thomas Becker, Bernd Hitzmann. Expert
  Systems With Applications 2014. 41 p. .
- [Jurgen Branke et al. ()] 'Automated Design of Production Scheduling Heuristics: A Review'. S N Jurgen Branke
   , Christoph Pickardt , Mengjie Zhang . *Ieee Transactions on Evolutionary Computation* 2016. 20 p. .
- [Jurgenbranke et al. ()] 'Automated Design of Production Scheduling Heuristics: A Review'. S N Jurgenbranke
   , Christoph Pickardt , Mengjie Zhang . *Ieee Transactions on Evolutionary Computation* 2016. 20 p. .
- (Jurgen Branke et al. ()) 'Automated Design of Production Scheduling Heuristics: A Review'. S N Jurgen Branke
   , Christoph Pickardt , Mengjie Zhang . *Ieee Transactions on Evolutionary Computation* 2016. 20 p. .
- [Jurgenbranke et al. ()] 'Automated Design of Production Scheduling Heuristics: A Review'. S N Jurgenbranke
   , Christoph Pickardt , Mengjie Zhang . *Ieee Transactions on Evolutionary Computation* 2016. 20 p. .
- [Kaban et al. ()] 'Comparison of Dispatching Rules in Job-Shop Scheduling Problem using Simulation: A Case
   Study'. A K Kaban , Z Othman , D S Rohmah . Int J Simul Model 2012. 2012. p. 12.
- [Kaban et al. ()] 'Comparison of Dispatching Rules in Job-Shop Scheduling Problem using Simulation: a Case
  Study'. A K Kaban , Z Othman , D S Rohmah . Int J Simul Model 2012. 2012. p. 12.
- [Elkhyari and Narendra Jussien ()] Constraint Programming for Dynamic Scheduling Problems, Abdallah
   Elkhyari , C G Narendra Jussien . Http://Www.Emn.Fr/Jussien/Publications 2003.
- [Elkhyari and Narendra Jussien ()] Constraint Programming for Dynamic Scheduling Problems, Abdallah
   Elkhyari , C G Narendra Jussien . Http://Www.Emn.Fr/Jussien/Publications 2003.
- [Maschiettoa et al. ()] 'Crane Scheduling Problem With Non-Interference Constraints in A Steel Coil Distribu tion Center'. Gabriela N Maschiettoa , Y O Martin , G Ravetti , Mauricio C De Souza . International Journal
   of Production Research 2016.
- [Maschiettoa et al. ()] 'Crane Scheduling Problem With Non-Interference Constraints in a Steel Coil Distribution
   Center'. Gabriela N Maschiettoa , Y O Martin , G Ravetti , Mauricio C De Souza . International Journal Of
   *Production Research* 2016.
- <sup>457</sup> [Heger et al. ()] 'Dynamic Adjustment of Dispatching Rule Parameters in flow Shops With Sequence Dependent
   <sup>458</sup> Setup Times'. J Heger , Branke , Jurgen , Hildebrandt , Torsten , Bernd Scholz-Reiter . International Journal
   <sup>459</sup> of Production Research 2016.
- <sup>460</sup> [Heger et al. ()] 'Dynamic Adjustment of Dispatching Rule Parameters in flow Shops with Sequence Dependent
   <sup>461</sup> Setup Times'. J Heger , Branke , Jurgen , Hildebrandt , Torsten , Bernd Scholz-Reiter . International Journal
   <sup>462</sup> of Production Research 2016.
- 463 [Barták ()] Dynamic Constraint Models for Planning And Scheduling Problems, R Barták . 1999. Grant Agency.
- <sup>464</sup> [Li and Xiao ()] 'Dynamic Parts Scheduling in Multiple Job Shop Cells Considering Intercell Moves And Flexible
   <sup>465</sup> Routes'. Dongni Li , YW , Guangxue Xiao . Computers & Operations Research 2013. 40 p. . (Jiafu Tang)
- [Li and Xiao ()] 'Dynamic Parts Scheduling in Multiple Job Shop Cells Considering Intercell Moves and Flexible
   Routes'. Dongni Li , YW , Guangxue Xiao . Computers & Operations Research 2013. 40 p. . (Jiafu Tang)
- [Zhang et al. ()] 'Dynamic Rescheduling in Fms that is Simultaneously Considering Energy Consumption and
   Schedule Efficiency'. Liping Zhang, X L Liang Gao, Guohui Zhang. The International Journal of Advanced
   Manufacturing Technology 2013. 87 p.
- 471 [Zhang et al. ()] 'Dynamic Rescheduling in Fms that is Simultaneously Considering Energy Consumption And
- 472 Schedule Efficiency. the'. Liping Zhang , X L Liang Gao , Guohui Zhang . International Journal of Advanced
   473 Manufacturing Technology 2013. 87 p. .

#### 21 J) COMPARISON OF DYNAMIC SCHEDULING TECHNIQUES

- 474 [Tarun Kanti Jana et al. ()] 'Dynamic Schedule Execution in an Agent Based Holonic Manufacturing System'.
- B B Tarun Kanti Jana , Soumen Paul , Bijan Sarkar , Jyotirmoy Saha . Journal of Manufacturing Systems
  2013. 32 p. .
- [Tarun Kanti Jana et al. ()] 'Dynamic Schedule Execution in an Agent based Holonic Manufacturing System'.
  B B Tarun Kanti Jana , Soumen Paul , Bijan Sarkar , Jyotirmoy Saha . *Journal of Manufacturing Systems* 2013. 32 p. .
- [Tarun Kanti Jana et al. ()] 'Dynamic Schedule Execution In an Agent Based Holonic Manufacturing System'.
  B B Tarun Kanti Jana , Soumen Paul , Bijan Sarkar , Jyotirmoy Saha . *Journal of Manufacturing Systems* 2013. 32 p. .
- <sup>483</sup> [Tarun Kanti Jana et al. ()] 'Dynamic Schedule Execution in an Agent Based Holonic Manufacturing System'.
  <sup>484</sup> B B Tarun Kanti Jana , Soumen Paul , Bijan Sarkar , Jyotirmoy Saha . *Journal of Manufacturing Systems*<sup>485</sup> 2013. 32 p. .
- [Zaki Ahmad Khan and Mahfooz ()] 'Dynamic Scheduling Algorithm for Variants of Hypercube Interconnection
   Networks'. J S Zaki Ahmad Khan , Alam Mahfooz . Indian Journal of Science and Technology 2017. 10 p. .
- [Zaki Ahmad Khan and Mahfooz ()] 'Dynamic Scheduling Algorithm for Variants Of Hypercube Interconnection
   Networks'. J S Zaki Ahmad Khan , Alam Mahfooz . Indian Journal of Science and Technology 2017. 10 p. .
- <sup>490</sup> [Leng ()] 'Dynamic Scheduling in Rfid-Driven Discrete Manufacturing System by using Multi-Layer Network
   <sup>491</sup> Metrics As Heuristic Information'. Jiewu Leng , PJ . Journal of Intelligent Manufacturing 2017.
- <sup>492</sup> [Leng ()] 'Dynamic Scheduling in Rfid-Driven Discrete Manufacturing System by using Multi-Layer Network
   <sup>493</sup> Metrics As Heuristic Information'. Jiewu Leng , PJ . Journal of Intelligent Manufacturing 2017.
- <sup>494</sup> [Zhai et al. ()] 'Dynamic Scheduling of a Flow Shop With On-Site Wind Generation for Energy Cost Reduction
   <sup>495</sup> Under Real Time Electricity Pricing'. Yuxin Zhai , KB , Fu Zhao , John W Sutherland . Cirp Annals <sup>496</sup> Manufacturing Technology 2017. 66 p. .
- <sup>497</sup> [Zhai et al. ()] 'Dynamic Scheduling of A flow Shop with on-Site Wind Generation for Energy Cost Reduction
   <sup>498</sup> under Real Time Electricity Pricing'. Yuxin Zhai , KB , Fu Zhao , John W Sutherland . *Cirp Annals -* <sup>499</sup> Manufacturing Technology 2017. 66 p. .
- [Tubilla ()] Dynamic Scheduling of Manufacturing Systems with Setups And Random Disruptions, F Tubilla .
   2011. Massachusetts Institute of Technology (Phd Thesis)
- [Tubilla ()] Dynamic Scheduling of Manufacturing Systems With Setups And Random Disruptions, F Tubilla .
   2011. Massachusetts Institute of Technology (Phd Thesis)
- 504 [Barták ()] 'Dynamic Scheduling of Photolithography Process Based on Kohonen Neural Network'. R Barták .
- Journal of Intelligent Manufacturing Bing-Hai Zhou, X. L., Richard. Y. K.Fung (ed.) 1999. 2013. 101 p. .
   (Grant Agency)
- [Zhou et al. ()] 'Dynamic Scheduling Of Photolithography Process Based on Kohonen Neural Network'. Bing-Hai
   Zhou , X L Y K Richard , Fung . Journal of Intelligent Manufacturing 2013. 26 p. .
- <sup>509</sup> [Feldmann et al. ()] 'Dynamic Scheduling on Parallel Machines'. Anja Feldmann , J S Shang-Hua , Teng .
   <sup>510</sup> Theoretical Computer Science 1994. 130 p. 24.
- <sup>511</sup> [Feldmann et al. ()] 'Dynamic Scheduling on Parallel Machines'. Anja Feldmann , J S Shang-Hua , Teng .
   <sup>512</sup> Theoretical Computer Science 1994. 130 p. 24.
- [Wen and Chen ()] Dynamic Scheduling Optimization for Instance Aspect Handling In Workflows, Yiping Wen ,
   JL , Zhigang Chen . 2014. (Buqing Cao)
- [Wen and Chen ()] Dynamic Scheduling Optimization for Instance Aspect Handling In Workflows, Yiping Wen ,
   JL , Zhigang Chen . 2014. (Buqing Cao)
- [Rossi and Lanzetta ()] 'Dynamic Set-Up Rules for Hybrid flow Shop Scheduling With Parallel Batching
   Machines'. Andrea Rossi , AP , Michele Lanzetta . International Journal of Production Research 2013. 52 p. .
- [Rossi and Lanzetta ()] 'Dynamic Set-Up Rules for Hybrid Flow Shop Scheduling with Parallel Batching
   Machines'. Andrea Rossi , AP , Michele Lanzetta . International Journal of Production Research 2013. 52 p. .
- [Binodini Tripathy and Sasmita Kumari Padhy ()] 'Dynamic Task Scheduling using A Directed Neural Network'.
   S D Binodini Tripathy , Sasmita Kumari Padhy . Journal of Parallel And Distributed Computing 2015. 75 p.
   .
- [Binodini Tripathy and Sasmita Kumari Padhy ()] 'Dynamic Task Scheduling using a Directed Neural Network'.
   S D Binodini Tripathy , Sasmita Kumari Padhy . Journal of Parallel and Distributed Computing 2015. 75 p.
   .
- [Lu et al. ()] 'Energy-Efficient Permutation flow Shop Scheduling Problem using a Hybrid Multi-Objective
   Backtracking Search Algorithm'. Chao Lu , LG , Xinyu Li , Quanke Pan , Qi Wang . Journal of Cleaner
   *Production* 2017a. 144 p. .

- [Lu et al. ()] 'Energy-Efficient Permutation flow Shop Scheduling Problem using A Hybrid Multi-Objective
   Backtracking Search Algorithm'. Chao Lu , LG , Xinyu Li , Quanke Pan , Qi Wang . Journal Of Cleaner
- 532 Production 2017a. 144 p. .
- [Hamzadayi ()] 'Event Driven Strategy Based Complete Rescheduling Approaches for Dynamic M Identical
   Parallel Machines Scheduling Problem with a Common Server'. Alper Hamzadayi , GY . Computers &
   Industrial Engineering 2016. 91 p. .
- [Hamzadayi ()] 'Event Driven Strategy Based Complete Rescheduling Approaches for Dynamic M Identical
   Parallel Machines Scheduling Problem with a Common Server'. Alper Hamzadayi , GY . Computers &
   Industrial Engineering 2016. 91 p. .
- [Pickardt et al. ()] 'Evolutionary Generation of Dispatching Rule Sets For Complex Dynamic Scheduling Problems'. Christoph W Pickardt, TH, Jurgen Branke, Jens Heger, Bernd Scholz-Reiter. International Journal of Production Economics 2013. 145 p. .
- [Pickardt et al. ()] 'Evolutionary Generation of Dispatching Rule Sets for Complex Dynamic Scheduling Problems'. Christoph W Pickardt, TH, Jurgen Branke, Jens Heger, Bernd Scholz-Reiter. International Journal of Production Economics 2013. 145 p. .
- [Wang et al. ()] Flexible Job Shop Scheduling Problem using an Improved Ant Colony Optimization, Lei Wang ,
   JC , Ming Li , Zhihu Liu . 2017. 2017 p. .
- [Wang et al. ()] Flexible Job Shop Scheduling Problem using an Improved Ant Colony Optimization, Lei Wang ,
   JC , Ming Li , Zhihu Liu . 2017. 2017 p. .
- [María González-Neira and Barrera ()] 'Flow-Shop Scheduling Problem under Uncertainties: Review and
   Trends'. Eliana María González-Neira , AR , M.-T , David Barrera . International Journal of Industrial
   Engineering Computations 2017. p. .
- [María González-Neira and Barrera ()] 'flow-Shop Scheduling Problem under Uncertainties: Review and Trends'.
   Eliana María González-Neira , AR , M.-T , David Barrera . International Journal of Industrial Engineering
   Computations 2017. p. .
- [Omara and Arafa ()] 'Genetic Algorithms for Task Scheduling Problem'. F A Omara , M M Arafa . Journal of
   Parallel and Distributed Computing 2010. 70 p. .
- [Omara and Arafa ()] 'Genetic Algorithms for Task Scheduling Problem'. F A Omara , M M Arafa . Journal of
   Parallel and Distributed Computing 2010. 70 p. .
- <sup>559</sup> [Herrmann ()] Handbook of Production Scheduling University of Maryland, J W Herrmann . 2006. College Park,
   <sup>560</sup> Sprineger.
- [Herrmann ()] Handbook of Production Scheduling University of Maryland, J W Herrmann . 2006. College Park,
   Sprineger.
- <sup>563</sup> [Joseph et al. ()] 'Handbook of Scheduling. Scheduling Real-Time Tasks'. Y-T Joseph , Leung"sanjoy , J G
   <sup>564</sup> Baruah . Algorithms And Complexity 2004. Crc Press Llc.
- <sup>565</sup> [Joseph et al. ()] 'Handbook of Scheduling. Scheduling Real-Time Tasks'. Y-T Joseph , Leung''sanjoy , J G
   <sup>566</sup> Baruah . Algorithms and Complexity 2004. Crc Press Llc.
- [Abedi ()] 'Hybrid Scheduling and Maintenance Problem using Artificial Neural Network Based Meta-Heuristics'.
   Mehdi Abedi , HS . Journal of Modelling in Management 2017. p. . (Hamed Fazlollahtabar)
- [Abedi ()] 'Hybrid Scheduling and Maintenance Problem Using Artificial Neural Network Based Meta-Heuristics'.
   Mehdi Abedi , HS . Journal of Modelling In Management 2017. p. . (Hamed Fazlollahtabar)
- [Terekhov and Tran ()] Integrating Scheduling And Queueing for Dynamic Scheduling Problems, Daria Terekhov
   JC B , Tony T Tran . 2010.
- 573 [Terekhov and Tran ()] Integrating Scheduling and Queueing for Dynamic Scheduling Problems, Daria Terekhov 574 , JC B , Tony T Tran . 2010.
- 575 [Kaminsky ()] P Kaminsky . Models and Algorithms for Integrated multi-Stage Production/ Distribution Systems:
- Third Party Logistics. Nsf Design, Service, Andmanufacturing Grantees and Research Conference, (St.
   Louis, Missouri Grant #Dmi -0200439) 2006.
- [Kaminsky ()] P Kaminsky . 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) 2006.
- [Shahzad ()] 'Learning Dispatching Rules for Scheduling: A Synergistic View Comprising Decision Trees'. Atif
   Shahzad , NM . Tabu Search and Simulation. Computers 2016. 5 p. 3.
- [Shahzad ()] 'Learning Dispatching Rules for Scheduling: a Synergistic View Comprising Decision Trees'. Atif
   Shahzad , NM . Tabu Search and Simulation. Computers 2016. 5 p. 3.

- 585 [Rakesh Kumar ()] 'Multi Agents Approach for Job Shop Scheduling Problem using Genetic Algorithm and
- Variable Neighborhood Search Method'. M A Rakesh Kumar . The 20th World Multi-Conference on Systemics,
   Cybernetics And Informatics Wmsci, (Haryana) 2016.
- [Rakesh Kumar ()] 'Multi Agents Approach for Job Shop Scheduling Problem using Genetic Algorithm and
   Variable Neighborhood Search Method'. M A Rakesh Kumar . The 20th World Multi-Conference on Systemics,
   Cybernetics and Informatics Wmsci, (Haryana) 2016.
- [Adibi ()] 'Multi-Objective Scheduling of Dynamic Job Shop using Variable Neighborhood Search'. M A Adibi ,
   MZ , M . Expert Systems with Applications Amiri 2010. 37 p. .
- [Adibi ()] 'Multi-Objective Scheduling of Dynamic Job Shop using Variable Neighborhood Search'. M A Adibi ,
   MZ , M . Expert Systems with Applications Amiri 2010. 37 p. .
- [Madureira et al. ()] 'Negotiation Mechanism for Self-Organized Scheduling System with Collective Intelligence'.
   A Madureira , IP , P Pereira , A Abraham . Neurocomputing 2014. 132 p. .
- [Madureira et al. ()] 'Negotiation Mechanism for Self-Organized Scheduling System with Collective Intelligence'.
   A Madureira , IP , P Pereira , A Abraham . Neurocomputing 2014. 132 p. .
- [Pach et al. ()] 'Orca-Fms: A Dynamic Architecture for the Optimized and Reactive Control of Flexible
   Manufacturing Scheduling'. Cyrille Pach , TB , Therese Bonte , Damien Trentesaux . Computers in Industry
   2014. 65 p. .
- [Pach et al. ()] 'Orca-Fms: A Dynamic Architecture for the Optimized And Reactive Control of Flexible
   Manufacturing Scheduling'. Cyrille Pach , TB , Therese Bonte , Damien Trentesaux . Computers In Industry
   2014. 65 p. .
- [Kalinowski Krzysztof and Cezary ()] 'Predictive -Reactive Strategy for Real time Scheduling of Manufacturing
   Systems' K D Kalinowski Krzysztof , Grabowik Cezary . Applied Mechanics and Materials 2013. 307 p. .
- [Kalinowski Krzysztof and Cezary ()] 'Predictive -Reactive Strategy for Real Time Scheduling of Manufacturing
   Systems'. K D Kalinowski Krzysztof , Grabowik Cezary . Applied Mechanics and Materials 2013. 307 p. .
- [Priore et al. ()] Paolo Priore , DD L F , Raúl Pino , Javier Puente . Dynamic Scheduling of Flexible
   Manufacturing Systems using Neural Networks and Inductive Learning, 2001.
- [Priore et al. ()] Paolo Priore , DD L F , Raúl Pino , Javier Puente . Dynamic Scheduling of Flexible
   Manufacturing Systems using Neural Networks and Inductive Learning, 2001.
- [Cataldo and Scattolini ()] 'Production Scheduling of Parallel Machines with Model Predictive Control'. Andrea
   Cataldo , AP , Riccardo Scattolini . Control Engineering Practice 2015. 42 p. .
- [Cataldo and Scattolini ()] 'Production Scheduling of Parallel Machines with Model Predictive Control'. Andrea
   Cataldo , AP , Riccardo Scattolini . Control Engineering Practice 2015. 42 p. .
- [Cataldo and Scattolini ()] 'Production Scheduling of Parallel Machines with Model Predictive Control'. Andrea
   Cataldo , AP , Riccardo Scattolini . *Control Engineering Practice* 2015. 42 p. .
- <sup>619</sup> [Cataldo and Scattolini ()] 'Production Scheduling of Parallel Machines with Model Predictive Control'. Andrea
   <sup>620</sup> Cataldo , AP , Riccardo Scattolini . *Control Engineering Practice* 2015. 42 p. .
- [Terekhova ()] Queueing-Theoretic Approaches for Dynamic Scheduling: A Survey, Daria Terekhova , DG D A
   J C B . 2014.
- [Terekhova ()] Queueing-Theoretic Approaches for Dynamic Scheduling: A Survey, Daria Terekhova , DG D A
   J C B . 2014.
- [Zhao and Xu ()] 'Real-Time Dynamic Hoist Scheduling for Multistage Material Handling Process Under
   Uncertainties' Chuanyu Zhao , JF , Qiang Xu . Aiche Journal 2013. 59 p. .
- [Zhao and Xu ()] 'Real-Time Dynamic Hoist Scheduling For Multistage Material Handling Process under
   Uncertainties'. Chuanyu Zhao , JF , Qiang Xu . Aiche Journal 2013. 59 p. .
- <sup>629</sup> [Priore et al. ()] 'Real-Time Scheduling of Flexible Manufacturing Systems using Support Vector Machines and
   <sup>630</sup> Case-Based Reasoning'. Paolo Priore , RP , Jose Parreño , Javier Puente . Business And Management 2015.
   <sup>631</sup> 3. (Journal of Economics)
- [Priore et al. ()] 'Real-Time Scheduling of Flexible Manufacturing Systems using Support Vector Machines And
   Case-Based Reasoning'. Paolo Priore , RP , Jose Parreño , Javier Puente . Business and Management 2015.
   (Journal of Economics)
- [Li Yuqing and Xu Minqiang ()] 'Rescheduling of Observing Spacecraft using Fuzzy Neural Network and Ant
   Colony Algorithm'. W R Li Yuqing , Xu Minqiang . *Chinese Journal of Aeronautics* 2014. 27 p. .
- [Li Yuqing and Xu Minqiang ()] 'Rescheduling of Observing Spacecraft using Fuzzy Neural Network and Ant
   Colony Algorithm'. W R Li Yuqing , Xu Minqiang . *Chinese Journal of Aeronautics* 2014. 27 p. .

- [Sana Alyaseri ()] K R Sana Alyaseri , K.-M. Http://Www.Uum.Edu.My Multi Objective Bee Colony Optimiza tion Framework for Grid Job Scheduling. the 4th International Conference on Computing and Informatics,
   2013.
- [Sana Alyaseri ()] K R Sana Alyaseri , K.-M. Http://Www.Uum.Edu.My Multi Objective Bee Colony Optimiza tion Framework for Grid Job Scheduling. the 4th International Conference on Computing and Informatics,
- 644 2013.
- [Gomes ()] Selection Constructive Based Hyper-Heuristic for Dynamic Scheduling, S R P Gomes . 2014. (Master
   Degree)
- [Gomes ()] Selection Constructive Based Hyper-Heuristic for Dynamic Scheduling, S R P Gomes . 2014. (Master
   Degree)
- 649 [Pereira ()] Self-Optimization Module For Scheduling Using Case-Based Reasoning, I Pereira, AM. 2013.
- 650 [Pereira ()] Self-Optimization Module for Scheduling using Case-Based Reasoning, I Pereira, AM. 2013.
- [Barbosa Da et al. ()] 'Simulation Study of Dispatching Rules in Stochastic Job Shop Dynamic Scheduling'. Edna
- Barbosa Da , M G C Silva , Marilda F´atima De Souza Da , Fabio Henrique Silva , Pereira . World Journal
   of Modelling and Simulation 2014. 10 p. 11.
- <sup>654</sup> [Baykaso?lu ()] 'Solving Comprehensive Dynamic Job Shop Scheduling Problem by using a Grasp-Based
   <sup>655</sup> Approach'. Adil Baykaso?lu , FS K . *International Journal of Production Research* 2017. 55 p. .
- <sup>656</sup> [Baykaso?lu ()] 'Solving Comprehensive Dynamic Job Shop Scheduling Problem by using A Grasp-Based
   <sup>657</sup> Approach'. Adil Baykaso?lu , FS K . International Journal of Production Research 2017. 55 p. .
- <sup>658</sup> [Ouelhadj ()] 'Survey of Dynamic Scheduling In Manufacturing Systems'. D Ouelhadj , PS . Journal of Scheduling
   <sup>659</sup> 2009. p. 27.
- [Ouelhadj ()] 'Survey of Dynamic Scheduling in Manufacturing Systems'. D Ouelhadj , PS . Journal of Scheduling
   2009. p. 27.
- [Balicki ()] 'Tabu Programming For Multiobjective Optimization Problems'. J Balicki . Ijcsns International
   Journal of Computer Science And Network Security 2007. 7.
- [Balicki ()] 'Tabu Programming for Multiobjective Optimization Problems'. J Balicki . Ijcsns International
   Journal of Computer Science and Network Security 2007. 7.
- [Kenny et al. ()] Towards Solving Large-Scale Precedence Constrained Production Scheduling Problems in Mining,
   Angus Kenny , XL , Andreas T Ernst , Dhananjay Thiruvady . 2017. p. .
- [Kenny et al. ()] Towards Solving Large-Scale Precedence Constrained Production Scheduling Problems in Mining,
   Angus Kenny , XL , Andreas T Ernst , Dhananjay Thiruvady . 2017. p. .