

Multi-objective optimization of production scheduling with evolutionary computation: A review**Robert Ojstersek^{a*}, Miran Brezocnik^a and Borut Buchmeister^a**^a*Faculty of Mechanical Engineering, University of Maribor, Slovenia***CHRONICLE***Article history:*

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ABSTRACT

Multi-Objective (MO) optimization is a well-known research field with respect to the complexity of production planning and scheduling. In recent years, many different Evolutionary Computation (EC) methods have been applied successfully to MO production planning and scheduling. This paper is focused on making a review of MO production scheduling methods, starting from production scheduling presentation, notation and classification. The research field of EC methods is presented, then EC algorithms' classification is introduced for the purpose of production scheduling optimization. As a main goal, MO optimization is focused on hybrid EC methods, and presenting their advantages and limitations. Finally, a survey of five scientific databases is presented, with the analysis of the scientific publications the terminology development of the scientific field is presented. Using the citation analysis of the scientific publications, the application for the MO optimization in manufacturing scheduling is discussed.

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1. Introduction

The focus of production optimization is moving increasingly from mass production to mass customization. The production planning and scheduling of such production systems is very important, due to competitive business conditions. Short production times of orders, high reliability of delivery times, low stocks, high flexibility (Yang & Takakuwa, 2017) and a favourable cost-time profile (Rivera & Chen, 2007), are linked to the manufacturing value flow, and they are becoming the key production goals, which can be achieved mainly with appropriate MO production optimization (Ojstersek & Buchmeister, 2017). The main goals indicate cost savings through rational and continuous use of working assets, materials and contractors. Stochastic arrivals of orders, different sequences, and the high-mix low-volume production system, can lead to a very uneven capacity utilization, resulting in a longer flow time of operations and in the deviation of delivery times. The essence of the problem lies in the well-founded way to create a queue of orders for all jobs in a short time. The introduction of modern technologies, supported by the concept of Industry 4.0 (Marilungo et al., 2017; Bartodziej, 2016), brings into production processes new challenges that require sophisticated, innovative and revolutionary solutions, especially in the field of MO production optimization. Pinedo (2005), presents in his book the importance of transferring the theoretical methods and knowledge of production planning and scheduling to

* Corresponding author
 E-mail: robert.ojstersek@um.si (R. Ojstersek)

application solutions. The presented methods (Pinedo, 2012) provide the basis for the areas of planning, scheduling and optimization of production systems. The methods and algorithms of production system optimization are presented as a user manual for the design of production facilities (Sule, 2008). Application solutions enable the realization of basic ideas, supported by theories, algorithms and systems (Pinedo, 2012). Researchers present various approaches for production system performance analysis, based on the used algorithms and approaches (Altiok, 2012), in order to evaluate the production system optimization methods. With the development of new technologies and the rapid complexity growth of the production systems, the need for using Evolutionary Computation (EC) methods (Bäck et al., 1997) is increasing for the purpose of solving Nondeterministic Polynomial-time hard problems (NP-hard) (Du & Leung, 1990). The optimization models are divided into deterministic ones, which can be described precisely by mathematical models and stochastic ones, which are described as NP-hard models. Both groups of models can be solved as static problems, e.g. using the Monte Carlo method, or dynamic (Hinderer et al., 2016), where we use continuous or discrete models. Researchers focus primarily on solving single-objective problems, which are based on determining a satisfactory solution of only one objective. In doing so, other objectives are considered as constants in a variable time interval. The optimization results led to unsatisfactorily obtained single-objective solutions, especially for NP-hard problems. In this case, we want to achieve better solutions in optimizing complex production systems, which leads to the use of MO methods in evolutionary approaches for the purpose of planning, scheduling and optimizing production systems (T'Kindt & Billaut, 2006; Nguyen et al., 2017). The basic MO methods are supplemented by the use of Genetic Programming (GP), where genetic algorithms are crucial. Genetic algorithms lead to sophisticated solutions to optimize the operation of machine tools and to place orders and jobs in an optimized production system (Askin & Standridge, 1993). Planning and scheduling in geographical area refers, in particular, to small and medium enterprises (Buchmeister & Palcic, 2015), which are very important all around the world, from smaller high-mix low-volume enterprises to mass production enterprises. During the rapid growth of mass production, the market became saturated with less quality widely available products. The last trends of mass production have, recently, been transformed into mass customization production, as more consumers want something different, something personal.

2. Production scheduling

Production planning and scheduling are defined as decision-making processes that are used on a daily basis in many production and service enterprises. The importance of the decisions taken is, consequently, reflected in the fields of jobs orders, production, transport and distribution of the final products (Becker & Scholl, 2009). Production scheduling is the process of optimizing, controlling and determination of the limited production system resources (machines, humans, finances etc.).

2.1. Notation

A notation presented by Graham et al. (1979) will be presented next.

i	job ($i = 1, \dots, n$)
j	machine ($j = 1, \dots, m$)
k	operation ($k = 1, \dots, o_i$)
h	resource ($h = 1, \dots, s$)
n	number of jobs
m	number of machines
o_i	number of operations of job J_i
s	number of limited resources
p_i, p_{ij}	processing time of job J_i on machine M_j
p_{ik}, p_{ikj}	processing time of operation O_{ik} on M_j

r_i	release date of job J_i
d_i	due date of job J_i
w_i	weight of job J_i importance

2.2. Classification

Table 1 presents production scheduling classifications made by Graham et al. (1979), which have made the production scheduling classification in three fields: Shop environment, job characteristics and optimality criteria.

Table 1

Classification of production scheduling

<i>Shop environment</i>		<i>Optimality criteria</i>	
I	Single machine	C_j	Completion time
O	Open shop	L_i/L_{max}	Lateness/maximum lateness
F	Flow shop	T_i/T_{max}	Tardiness/maximum tardiness
FF	Flexible Flow shop	U_i	Unit penalty
AF	Assembly Flow shop	C_{max}	Makespan
J	Job shop	$\sum C_j$	Total completion time
JF	Flexible job shop	$\sum (d_i - C_i)$	Total earliness
P	P identical machines in parallel	$\sum T_i$	Total tardiness
Q	Q machines in parallel with different speeds	$\sum U_i$	Number of late jobs
R	R unrelated machines in parallel	$\sum w_i C_j$	Total weighted completion time
		$\sum w_i U_j$	Weighted number of tardy jobs
		$\sum w_i T_i$	Total weighted tardiness
		$\sum w_i (d_i - C_i)$	Total weighted earliness

Planning and scheduling in the production systems are based on mathematical and heuristic methods (Meolic & Brezocnik, 2018), which enable the proper distribution of limited production capacities according to the necessary production activities (Mirshekarian & Šormaz, 2016). Production activities must be carried out in such a way that the company optimizes its performance while achieving the set goals (Alghazi, 2017). The importance of planning and scheduling job shop production is reflected in a broad, yet deepened research field. Job shop production is one of the most active research areas in the planning and scheduling of production systems. The frequency of the job shop type production systems worldwide is the basis for all other production systems types in the field of Planning, Scheduling and Optimization, from small to large enterprises. The mentioned type of production is most often seen in the production of a small number of products where the subscriber can choose the characteristics of the product himself. Due to dynamic product changes, optimization problems are defined as NP-hard problems. Scheduling of job shop production is defined by four main research problems:

- Job Shop Scheduling Problem (JSSP),
- Flexible Job Shop Scheduling Problem (FJSSP),
- Dynamic Job Shop Scheduling Problem (DJSSP),
- Flow Shop Scheduling Problem (FSSP).

Their characteristics are:

JSSP: In a production system we have n orders J_1, J_2, \dots, J_n with different process times. Individual tasks must be performed on m machines that can be different from one another. The tasks must be performed according to the previously specified sequence of operations. In solving the JSSP problem, we focus on reducing the total makespan of orders (C_{max}) (Pinedo, 2005), the calculation is represented by the Eq. (1).

$$C_{max} = \max \{C_i\}, 1 \leq i \leq n \quad (1)$$

In Eq. (1) the C_i presents the time of determining the task $i, i = 1, \dots, n$.

FJSSP: Is a more realistic derivative of the JSSP, where jobs can be performed on machines from a set of machines suitable for carrying out the jobs. The choice of the machine is made according to the occupancy of the machine and the suitability of the machine to perform the operation. The number of jobs and number of machines are given. Each job has a specific sequence of operations, and operations can only be performed on individual machines. The processing time of the operation may vary, depending on the machine on which it is running, and the machine can only perform one operation at a time. At FJSSP, we can optimize several objectives at the same time, for example: Total flow time, total tardiness, total lateness, maintenance time, makespan, etc.

DJSSP: Unlike JSSP, which represents a static optimization problem, the DJSSP is a dynamic optimization problem. It is characterized by dynamic production system models, such as: Random arrivals of orders, accidental machine failures, changes in production times, etc. Dynamic variables represent a more realistic optimization problem, whose solutions can be transferred easily directly to real-world applications (Tasic et al., 2007).

FSSP: Is the optimization problem in which we want to optimize the sequence of individual orders on available machines. We have m orders that we want to implement on n available machines. Each job has a precisely determined number of n operations, which are all in the same sequence. The i^{th} operation must be performed on the i^{th} machine. Each machine can only perform one operation, the time of which is specified. FSSP is a typical representative of an MO optimization problem, in which we most often optimize the following parameters: Average flow time $\sum w_i F_i$, time of execution of all C_{max} orders, and total tardiness of orders $\sum w_i T_i$. W_i represents the vector of weights, $i = 1, \dots, n$, where the operative weight i represents the relative importance of the operation from the point of the optimization objective. The optimization parameters are calculated with equation (2), which represents the calculation of the average flow time.

$$F = 1/n \times \sum (C_i - S_i), i = 1, \dots, n \quad (2)$$

In this case, C_i represents the execution time of the task $i, i = 1, \dots, n$, S_i is the starting time of execution of the task. The time of execution of all orders is represented by Eq. (1). The tardiness of the orders is calculated with Eq. (3).

$$T_i = \max \{0, C_i - d_i\} \quad (3)$$

The d_i parameter presents the due date of the order i .

Regarding the optimization problems presented above, it can be assumed that the planning and scheduling of job shop production present the basic concepts and methods that are very important for the other types of production processes optimization (Xu et al., 2013). For the most common cases, we use heuristic algorithms, which serve as decision-making systems for real-time order management in a production environment (Saha et al., 2016). The aforementioned algorithms are based mostly on the use of EC, the results of which show satisfactory solutions. Researchers most often solve planning and scheduling problems by introducing the theory of Particle Swarm Optimization (Shi & Eberhart, 1999), Neural Networks, Fuzzy Logic, and Genetic Algorithms (Rajasekaran & Pai, 2003). For modelling, simulating and application, researchers use various software tools, which allow the transfer of theoretical knowledge to application solutions. Thus, in the field of Production Scheduling, a number of research subsections can be found on the order, which are related to convex optimization problems, as well as to

the design and introduction of new evolutionary methods. The knowledge that researchers use in this field is an interdisciplinary mix of the fields of Production Systems, EC and discrete event simulation methods.

3. Multi-objective optimization

MO optimization is an area that deals with MO decision-making of mathematically difficult optimization problems (Lin & Gen, 2018). Optimization problems include more than one target optimization function, where multiple variable functions need to be optimized at the same time. The characteristic of the MO optimization problem is that there is no single solution as the final result, which can, simultaneously, optimize a particular criterion (Miettinen, 2012). Therefore, in this case, the criterion functions are contradictory (Branke et al., 2008). For these functions, there is an unlimited number of Pareto optimal solutions (Deb et al., 2000). Pareto solutions are non-dominated, Pareto optimal, Pareto effective (Deb & Jain, 2014). All Pareto optimal solutions in the Pareto area solution are considered equally good.

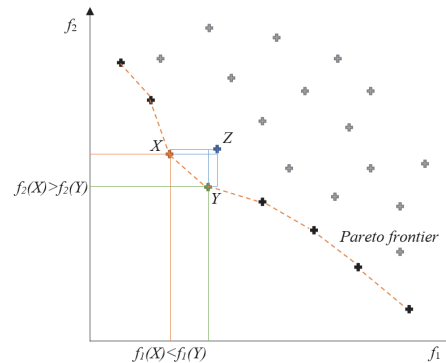


Fig. 1 Graph of Pareto frontier.

An example of the Pareto optimal solution for the functions f_1 and f_2 is presented on the two-dimensional graph in Figure 1, on which the quadratic points represent possible solutions. Point Z is not located in the Pareto solution, since it is dominated by points X and Y. Points X and Y are not dominated to each other, therefore both are in the Pareto frontier. The classification of MO decision-making optimization methods are presented in Table 2.

Table 2

Classification of MO decision-making optimization methods.

Type	Method	Algorithm	Abbreviations
A priori	Utility function method		
	Lexicographic method		
	Goal programming		
A posteriori	Mathematical programming	DSD	Direct Search Domain
		SPO	Successive Pareto Optimization
		NC	Normal Constrain
		NBI	Normal Boundary Intersection
	Evolutionary Computation	MOGA	Multi-Objective Genetic Algorithm
		MOPSO	Multi-Objective Particle Swarm Optimization
		SA	Simulated Annealing
		SPEA	Strength Pareto Evolutionary Algorithm
		NSGA-II	Non-dominated Sorting Genetic Algorithm-2
PESA-II	Pareto Envelope-based Selection Algorithm-2		
Interactive	Semi-interactive method		
	Progressively interactive method	NIMBUS	Nondifferentiable Interactive Multi-objective BUNDLE-based optimization System
		PI-EMO-VF	Evolutionary Multi-Objective algorithm using Value Function
Hybrid			

Hao et al. (2017) commission the use of MO optimization in the field of Production Scheduling, and bi-criteria optimization for the stochastic JSSP. The algorithm optimizes the average flow time and total tardiness of work orders. Combining heuristic methods and multi-criterion optimization (Pérez & Raupp, 2016; Hultmann et al., 2017) allows solving complex manufacturing processes. The basic algorithm is based on the application of priority rules and Genetic Algorithms (Huang & Süer, 2015). Further research work on EC, Particle Swarm theory and improved Genetic Algorithms leads to Pareto optimal solutions (Li et al., 2016; Wisittipanich & Kachitvichyanukul, 2013; Ripon et al., 2011). MO optimization is used, not only in the field of Production Planning and Scheduling, but MO algorithms also prove useful in the field of Machines and Devices' Location Planning (Lukic et al., 2017; Mousavi et al., 2017). Lately, great attention has been focused on the introduction of assessment methods for the purpose of MO production optimization. The researchers implement the Kalman algorithm method (Pakrashi & Chaudhuri, 2016; Ojstersek et al., 2017; Lin & Wang, 2013) as an evaluation method for determining Pareto optimal solutions by introducing a set of optimal solutions (optimal solutions' clustering) (Toscano & Lyonnet, 2012). The proposed introduction of evaluation methods improves Pareto optimal solutions significantly, since we choose the best from the whole set of solutions (Su et al., 2017). The problem of the proposed method is efficient only in low-demanding cases, but problems still occur in cases that are more complex, where the mathematical complexity of the algorithm is increased. The problem of the proposed method is efficient only in low-demanding cases, but problems still occur in cases that are more complex, where the mathematical complexity of the algorithm is increased (Ojstersek et al., 2019). The model considered is a randomly routed job shop. The manufacturing system consists of six workstations, and each workstation consists of one machine. Each job is assigned a random routing sequence, the processing time for each machine and the due date. The routing sequences assigned to jobs have an undirected flow. The assumptions of the manufacturing system are as follows: operations cannot be pre-empted; each machine can process only one task at a time; and, the queues are managed by the Earliest Due Date (EDD) policy to improve lateness performance. In this research, the material handling time is included in the machining time, and the handling resources are always available. The manufacturing system is characterized by one bottleneck, as described in Section 4.

3.1. Hybrid Multi-Objective Optimization

Optimization algorithms are divided into three major groups: Exact, approximating, and heuristic algorithms. Exact algorithms are designed so that the solution of the optimization problem is always optimal at a specific known time interval. The disadvantage of this group of algorithms is the difficulty of applying them to more complex optimization problems, i.e. NP-hard optimization problems. In this case, the time-end interval is exponentially longer with an additional problem dimension complexity. The second group are approximation algorithms, based on satisfactory solutions determined close to the optimal solutions (the differences between the solutions obtained and the optimal solution are known). Heuristic optimization algorithms, whose characteristic is that they do not find optimal solutions but satisfactorily good solutions (Pareto optimal solutions) in a shorter time than approximation algorithms, define the third group (Gen et al., 2015). Heuristic algorithms are intended for specific use on a particular problem, which must be described well mathematically (Sundar et al., 2017; Siddique, 2013). However, when we want to use heuristic algorithms on several different optimization algorithms applied on real world optimization problems, we are talking about metaheuristic algorithms (Zhang et al., 2017). Metaheuristic algorithms are designed for highly demanding NP-hard problems; in this case, algorithms give near optimum results (J. Li et al., 2016; Marinakis & Marinaki, 2012). Metaheuristic methods are defined as higher levels of epistemes, with which we can find, generate or determine near optimum solutions to applicative optimization problems (Glover & Kochenberger, 2006). We use metaheuristic methods in particular when we do not have all the desired system data available (Meeran & Morshed, 2014; Frutos et al., 2016), and in the case of limited processing power. Compared to the exact and approximating algorithms, with the metaheuristic algorithms we cannot provide global optimal solutions, and we do not know the error between the obtained and the optimal solution. Therefore, in many cases, we introduce various stochastic approaches into metaheuristic algorithms, which allow us to determine

the solutions according to a set of randomly generated variables (Kundakci & Kulak, 2016; Liu et al., 2008). For combinatorial optimization problems, such as production systems' planning and scheduling, metaheuristic algorithms are obtained with a satisfactory solution. Metaheuristic methods are presented satisfactorily in the following areas:

- Simultaneous scheduling of machines and transport robots in the FJSSP environment using a hybrid metaheuristic based on a clustered holonic multiagent model (Nouri et al., 2016).
- Improved heuristic Kalman algorithm for solving MO FJSSP, where researchers present a totally new approach for optimizing production system makespan, machine workload and workload of the most loaded machine (bottleneck determination) (Ojstersek et al., 2018).
- Hybrid algorithm based on priority rules for simulation of workshop production (Zupan et al., 2016).
- A bare-bones MO Particle Swarm Optimization algorithm for environmental economic dispatch (Zhang et al., 2012).
- Ant colony optimization system for a multi-quantitative and qualitative objective job shop parallel machine scheduling problem (Chang et al., 2008) etc.

The above mentioned methods are showing satisfactorily good solutions in the field of Production Planning and Scheduling as a method of MO optimization using different EC methods, like hybrid Genetic Algorithms (Gen et al., 2015). The weaknesses due to the lower robustness of the algorithm have been improved with the help of a Fuzzy Logic approach, Particle Swarm theory and Genetic Algorithms used to determine the optimal production and manufacturing layout (Wang et al., 2011).

4. Methodology

When reviewing the existing relevant scientific literature, we focused on a search with three appropriate selected keywords. The selected keywords were "multi-objective optimization", "production scheduling" and "evolutionary computation". Our search was limited to the five most relevant databases: Web of Science (WoS), ScienceDirect, Scopus, IEEE Xplore and Springer Link. The obtained results from January 2019 are presented in Table 3. The chosen search time for published publications was limited between 2005 and 2019. At that time, the mentioned three research areas were the most relevant and, thus, provided state-of-the-art research work results.

Table 3

Number of hits for "multi-objective optimization", "production scheduling" and "evolutionary computation"

Database	Hits
WoS	126
Science Direct	3345
Scopus	6814
Springer Link	2854
IEEE Xplore	25

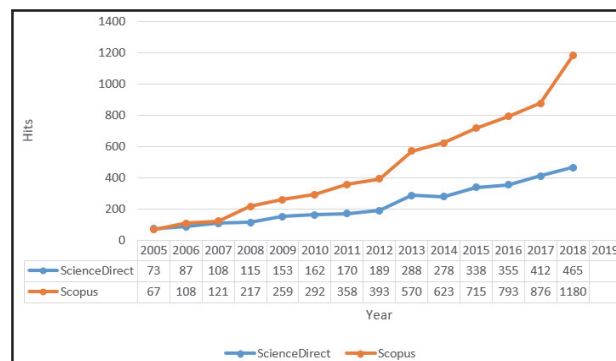


Fig. 2. Terminological development of research field regarding publication hits

Given the fact that Table 3 shows the number of scientific works published in the five most important databases, in Fig. 2, we want to show terminological development in the research field of Multi-objective Production Scheduling Optimization using evolutionary computation methods. The number of published works relates to two databases (ScienceDirect and Scopus). The results presented in the graph confirm the basic hypothesis about the development of the mentioned research field, since the publications of scientific works in recent years have been increasing. Particularly significant progress has been made since 2013 and to the present, since the number of annual publications has increased by 100 %. A positive trend in the growth of research publications in this field can also be expected in the future, as the current concept of Industry 4.0 is based on the applied application of the presented methods (Yao et al., 2017).

5. Evolutionary Computation in Production Scheduling

MO production systems' optimization is a very complex task. It is extremely difficult to solve it with conventional methods. That is why researchers use Evolutionary Computation (EC) methods and other approaches. Evolutionary Computation is fundamental for evolutionary algorithms, which are population-based metaheuristic optimization algorithms, constructed by four-step biological evolution: Reproduction, mutation, recombination and selection. Thus, the framework in Figure 3 can define the evolutionary computation methods generally as follows.

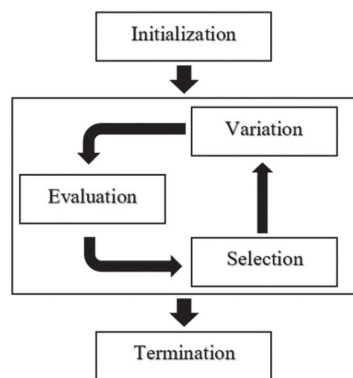


Fig. 3. Evolutionary computation methods' general framework

Generally, evolutionary computation methods are divided into Genetic Algorithms (GA) (Kramer, 2017; Mitchell, 1998), Genetic Programming (GP) (Al-Kazemi, 2002; Eberhart & Kennedy, 1995), Evolution Programming (EP) and Evolutionary Strategies (ES) (Yager & Filev, 1994) etc. GA, due to their advantages, are used for a wide range of discrete and combinatorial optimization problems, like traveller salesman problem, multiple knapsack problems (Shah-Hosseini, 2008), automated guided vehicle problem etc. In addition, they also have some limitations related to the difficulty in determining the initialization parameters, and, in some cases, the results do not represent optimal solutions.

Table 4

EC methods' classification with a summary of the advantages and limitations related to production scheduling literature

<i>EC methods</i>	<i>Advantages</i>	<i>Limitations</i>	<i>Application use</i>	<i>References</i>
GA	Good solver for combinatorial problems Wide range of obtained solutions	Difficult to obtain the optimal solution in all cases Hard to choose initial parameters	Discrete optimization	(Konak et al., 2006; Holland & Goldberg, 1989)
GP	Competes with neural nets and alike	Slow convergence Needs huge populations for efficient computation	Machine learning	(Lee & Asllani, 2004)
EP	Open framework Self-adaption of parameters	No recombination	Machine Learning, Optimization problems	(Marler & Arora, 2004)
ES	Fast optimising approach for real-valued optimization Self-adaption	Falling into local optimum More initial data needed	Numerical optimization	(Loukil et al., 2005)

Table 5
Summary of selected algorithms and their components sorted by proposed taxonomy

<i>Algorithm</i>	<i>Production Type</i>	<i>Initialization</i>	<i>Definition of Stop Condition</i>	<i>Advantages</i>	<i>Validation</i>
DDPSO (Zhao et al., 2014)	JSSP	Random	100 iterations	+ Decline disturbance index introduced. + High convergence speed. + Single and multi-objective optimization futures.	<ul style="list-style-type: none"> • Fisher and Thomson (ft06, ft10, ft20), • Lawrence (la01 – la36).
GA and constrain programming (Sioud et al., 2012)	JSSP	Pseudo-random	50000 iterations	+ Position domain set. + Pseudo-random transition rule. + Efficient hybrid crossover.	<ul style="list-style-type: none"> • Ragatz (15, 25, 35, 45 jobs), • Gagne (55, 65, 75, 85 jobs).
PSO and SA (Xia and Wu, 2005)	FJSSP	Random	4000 iterations	+ Look-ahead approach for improve solutions quality. + Good quality results in a reasonable time limit. + Multi-objective optimization futures.	<ul style="list-style-type: none"> • Kacem (8x8, 10x10, 15x10).
FL and EA (Kacem et al., 2002)	FJSSP	Localization	300 iterations	+ Biological concept of GMO for final solutions quality enhancement. + Strong representation capabilities of FL to control EAs.	<ul style="list-style-type: none"> • Kacem (4x5, 10x7, 10x10, 15x10).
PSO and LS (Moslehi & Mahnam, 2011)	FJSSP	Random	120 iterations	+ Competitive solutions obtained at satisfactory computation times. + Medium-sized problem high efficiency.	<ul style="list-style-type: none"> • Kacem (4x5, 10x7, 10x10, 15x10).
MOEA-based Predictive-reactive Scheduling Method (Shen & Yao, 2015)	DJSSP	Heuristic strategies	20000 iterations	+ Dynamic multi-objective optimization model. + Shop efficiency and stability optimization approach. + Real-time events dynamic changes addressed.	<ul style="list-style-type: none"> • Initial 10x10 static FJSSP instance, • enhanced by MTBF and MTRR times for DJSSP.
HMOGWO (Lu et al., 2017)	DJSSP	Random and NEH method	100000 iterations	+ Multi-objective mathematical model with consisting three dynamic events. + Random generated instances with regard to convergence, spread and comprehensive metrics.	<ul style="list-style-type: none"> • Randomly generated, • number of jobs (20, 40, 60, 80, 100). • number of machines (4, 5, 6, 7, 8).
DDE algorithm (Pan et al., 2009)	FS	NEH and EDD heuristics	2000 iterations	+ No-wait flow shop scheduling approach. + Job-permutation-based encoding shame. + Pareto-based selection operator.	<ul style="list-style-type: none"> • Car01 – Car08, • Hell and Hel2, • Rec01 – Rec41.
HMOIA (Moghaddam et al., 2007)	FS	ETS	500 iterations	+ Useful comparison metrics. + Large-sized problem high efficiency.	<ul style="list-style-type: none"> • Self-proposed small and large-sized problems.

The second group of EC are GP methods, which are used primarily in Machine learning, where their limitation regarding slow convergence and the required large population size have less influence on the obtained solutions. Lately, in order to solve optimization problems, new methods of EP have appeared in Machine Learning, where the open framework, and the possibility of parameters' self-adaption, allows near optimal solutions with the limitation, due to the no recombination nature of the EP. In contrast to GP, the EC methods feature a fast optimization approach for real-value numerical optimizations. ES methods allow self-adaption, which generally requires more initialization parameters, which, in some cases, can lead to falling into the local optimums. In Table 4, we can see EC methods' division in 4 main groups. The Table summarises the advantages and limitations of the individual subgroups. The general-purpose use is defined, and key literature is given referring to the production scheduling in Table 5.

6. Applications

In a time of rapid development of companies that meet in the global market with the introduction of the Industry 4.0 concept based on mass personalization of customised products, MO optimization with EC is very important. That is why researchers want to test their optimization algorithms with the use of simulation methods for the purpose of production systems' modelling and analysing (Law et al., 2007), which defined the basic simulation methods. In order to optimise production, researchers use a wide range of software environments to analyse and optimise production processes (Leite, 2010; Joines & Roberts, 2013). Due to the wide range of different simulation methods and their advantages and disadvantages, it is essential that the correct choice of simulation methods is made with respect to the optimization problem's characteristics (Pegden, 2008). For the purpose of production system testing, researchers use activity-based simulation, in which time is broken up into small slices, and the system state is updated according to the set of activities happening in the time slice (Dehghanimohammadabadi & Keyser, 2017). Because discrete-event simulations do not have to simulate every time slice, they can, typically, run much faster than the corresponding continuous simulation (Fishman, 2013). Considering that, in Section 2, we presented the basic types of production problems, in this chapter we want to present how the theoretical models are transferred to real-world production systems. We have analysed 126 references from Table 3 in the WoS database, and differentiated them according to the type of production systems between JSSP, FJSSP, DJSSP, Flow Shop (FS) and evolutionary computation methods used in general optimization approaches for production systems. The results, shown in Figure 4, show that the majority of applicative EC methods are transferred to the general JSSP. Out of the total of 126, 20 of them solve this problem. Recently, publications in the field of FJSSP and DJSSP, which represent a more realistic type of production, are dominated according to the publication time. Together, they represent 22 publications, which, however, will definitely intensify, given the trend of increasing publications in the past years. Both of these production systems types represent a very active research area, where optimization methods of Evolutionary Computation and multi-objective optimization represent the basis for problem solutions. Flow Shop production type is also very active in the optimization area. The results in Figure 4 represent 15 % of all publications in the EC Production Scheduling field. The presented solutions show the advantage of the methods in the real-world applications. We have added some important references in Table 6. According to Figure 4, we can see that as many as 64 references are related to the general type of production systems. In this case, researchers perform experiments on benchmark cases, or they present general optimization approaches for solving various optimization problems, which can be usable for different types of production systems.

Table 6

Relevant references for production planning applications.

<i>JSSP</i>	<i>FJSSP</i>	<i>DJSSP</i>	<i>FS</i>	<i>General</i>
(Esquivel et al., 2002; Zhao et al., 2014; Sioud et al., 2012)	(Tay & Ho, 2008; Jia & Hu, 2014; Li et al., 2010; Li et al., 2011; Zhang et al., 2009; Singh & Mahapatra, 2016)	(Abello et al., 2011; Lu et al., 2017; Shen & Yao, 2015)	(Arroyo & Armentano, 2005; Murata et al., 1996; Ishibuchi & Murata, 1998)	(Klancnik et al., 2016; Xiang et al., 2015; Granja et al., 2014)

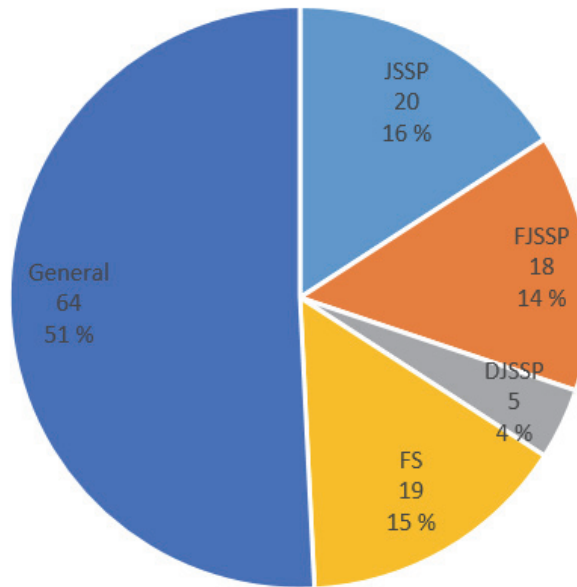


Fig. 4. Division of Evolutionary Computation methods according to the production type

7. Discussion

In this research work, we have presented the research field of Multi-objective Optimization using Evolutionary Computation methods in Production Scheduling. We have studied five scientific relevant databases systematically, using the three key words “multi-objective optimization”, “production scheduling” and “Evolutionary Computation”. Table 7 shows the number of citations in relation to the individual production type. Research was carried out with a detailed analysis of 126 references (Table 3) in the WoS database. We have found that most citations relate to solving the FJSSP, which can be attributed to its applicative nature and higher interest for solving it in recent years. With its citations, FJSSP represents 50.5 % of all citations within the 126 references. MO and EC methods used to solve general problems within Production Scheduling contribute up to 520 citations, representing 22.2 % of all citations. The activity and topicality of the field is also reflected in the Flow Shop optimization, where 408 citations represent 17.4 %. The smallest number of citations in this category are provided by JSSP (136 citations or 5.8 %) and DJSSP (95 citations or 4.1 %). JSSP, with its theoretical background, is the basis for testing new proposed methods and approaches, but it is used significantly less in more applied cases. Recently, when the concept of Industry 4.0 has been influencing the optimization of dynamic production systems increasingly (Shin et al., 2018), it also benefits from the DJSSP, which is reflected in the high activity of research work done in the recent period. The results presented in Table 7 show the activity and importance of multi-objective optimization investigation using evolutionary methods in Production Scheduling. Considering that the multi-objective production scheduling optimization is an NP-hard optimization problem, our survey confirmed the appropriateness of the use of Evolutionary Computation methods. The number of published research works has been increasing over recent years, and published research work is increasingly being transferred from conceptual methods to application solutions to real-world problems within production systems. Most recently, researchers have been focusing on flexible and dynamic production systems, for which multi-objective optimization is crucial.

The main purpose of this paper was the classification, presentation and evaluation of the published research work in the field of Multi-objective Optimization in Production Scheduling using the Evolutionary Computation methods. The main purpose was giving the current data on the citation,

topicality and applicative applicability of individual methods, with an emphasis on advantages and limitations. These data can serve readers as guidelines in their research work, based on which they can choose a research problem, methods, and they can evaluate effectiveness of the individual approach.

Table 7

Number of citations and most cited references.

	<i>JSSP</i>	<i>FJSSP</i>	<i>DJSSP</i>	<i>FS</i>	<i>General</i>
Number of citations	136	1183	95	408	520
Share (%)	5.8	50.5	4.1	17.4	22.2
Most cited	(Esquivel et al., 2002; Zhao et al., 2014; Sioud et al., 2012)	(Kacem et al., 2002; Xia & Wu, 2005; Moslehi & Mahnam, 2011)	(Lu et al., 2017; Abello et al., 2011; Shen & Yao, 2015)	(P. C. Chang et al., 2008; Tavakkoli-Moghaddam et al., 2007; Pan et al., 2009)	(Moon & Seo, 2005; Duhamel et al., 2011; Elloumi & Fortemps, 2010)

7.1. Issues and open questions

Our research has shown quite a few problems and differences in which open questions arise, which science will have to answer in the near future. The results presented confirm the hypothesis about the actuality of the research field, which, in the reflection of dynamic and flexible production systems, makes huge progress. The authors present their research work in two separate groups. Some researchers perform experiments on benchmark datasets (Palacios et al., 2016), while others perform their optimization algorithms in applied cases. In doing so, there is a problem of mutual evaluation and comparison, since, in some cases, it is impossible to transfer parallels.

Subsequently, a lot of research work has to be done on the research of fundamental methods, their robustness, and the transfer to applied cases. The help of algorithms' hybridization can link together individual algorithm advantages, and eliminate their limitations. Such a step, and the applicability of the proposed solutions, will enable the progress and development of the mentioned research area, which is gaining more and more attention at the expense of the increasingly complex industrial systems of Industry 4.0.

8. Conclusions

In this paper, we present a research survey based on MO optimization with EC methods for Production Scheduling problems, which reduces the gap in this research field. First, we presented the research field of Production Scheduling, notation and basic classification, supported by mathematical formulation.

We continued with the presentation of MO optimization and its classification, which are the basis for the advanced Production Scheduling. This section summarizes the main MO approaches, methods and algorithms. This is followed by the hybrid methods, which have recently been used more and more in the mentioned research field.

In the section Methodology, we presented a literature review in five relevant research databases (WoS, Scopus, ScienceDirect, IEEE Xplore and Springer link), where we have focused on the terminological development of the research area between 2005 and 2019. The results obtained confirm the basic hypothesis that the research field of Production Scheduling Multi-objective Optimization with the EC methods has been developing in recent years. The number of references found using three keywords "multi-objective optimization", "production scheduling" and "Evolutionary Computation" confirm this.

The use of EC methods for the purpose of Multi-objective Production Scheduling Optimization is presented, where we have shown the general framework used in EC methods. The basic division of EC methods is given, and individual advantages and limitations are presented. In Table 4, which summarizes the EC methods, we present the most important references in relation to Production Scheduling. The general applicability of the individual approach is defined.

The importance of transferring theoretical approaches, methods and algorithms to application examples is presented, where we present the analysis of the WoS database by dividing the Production Scheduling into four types of production systems (JSSP, FJSSP, DJSSP and Flow Shop). The distribution of references in the WoS database also includes general approaches for Multi-objective Production Scheduling Optimization. Depending on the individual production type, we propose guidelines for readers and researchers in the field, who can understand and find out the most appropriate approaches and current research area with the help of the cited data.

Given the fact that we presented the research field which, individually, represents three very topical problems (Multi-objective Optimization, Production Scheduling and Evolutionary Computation), we can claim that the researchers managed to connect them, and, thus, came up with new methods, approaches and solutions of application problems. Given the limitations presented, we can note that there is still a lot to be done in the research area, which will focus on solving the flexible, dynamic and self-adaptive production systems in the further development phase. In doing so, researchers will use methods of hybridization, simulation and mathematical modelling.

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