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Flow-shop scheduling problem under uncertainties: Review and trends

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A B S T R A C T

Among the different tasks in production logistics, job scheduling is one of the most important at the operational decision-making level to enable organizations to achieve competiveness. Scheduling consists in the allocation of limited resources to activities over time in order to achieve one or more optimization objectives. Flow-shop (FS) scheduling problems encompass the sequencing processes in environments in which the activities or operations are performed in a serial flow. This type of configuration includes assembly lines and the chemical, electronic, food, and metallurgical industries, among others. Scheduling has been mostly investigated for the deterministic cases, in which all parameters are known in advance and do not vary over time. Nevertheless, in real-world situations, events are frequently subject to uncertainties that can affect the decision-making process. Thus, it is important to study scheduling and sequencing activities under uncertainties since they can cause infeasibilities and disturbances. The purpose of this paper is to provide a general overview of the FS scheduling problem under uncertainties and its role in production logistics and to draw up opportunities for further research. To this end, 100 papers about FS and flexible flow-shop scheduling problems published from 2001 to October 2016 were analyzed and classified. Trends in the reviewed literature are presented and finally some research opportunities in the field are proposed.

1. Introduction

Logistics and supply chain concepts have evolved over the years, initially involving only transportation activities and then expanding to include product flows, information flows, and reverse flows until finally reverse flows, integrated chains, and networks were incorporated. Although there is diversity in definitions, there is a common understanding that logistics involves three principal stages called supply, production, and distribution (Farahani et al., 2014). Despite this taxonomy, many distribution and production problems share similar mathematical formulations and solution procedures. Due to the vast variety of problems and knowledge that all these stages comprise, we are going to focus on production

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logistics processes, with a particular view on scheduling of jobs and tasks. Indeed, many product distribution problems have been analyzed in the literature as transportation problems, but they can also be viewed as scheduling problems. So, scheduling activities are performed in at least two stages of the logistics system.

Generally speaking, scheduling consists in the allocation of limited resources to activities over time in order to optimize one or more desired objectives established by decision-makers. Both resources and activities can be of different types, so the theory of scheduling has many applications in manufacturing and services, playing a crucial role in the competitiveness of organizations and industries (Brucker, 2007; Leung et al., 2004; Pinedo, 2012). Scheduling problems can be classified depending on the configuration of resources (often called the production environment). Among the principal configurations, single-machine, parallel-machines, flow-shop (FS), flexible flow-shop (FFS), job-shop, flexible job-shop, and open-shop configurations can be found and can be analyzed in a deterministic or a stochastic way (Pinedo, 2012). Particularly, FS problems (including FFS) have been extensively studied due to their versatility and applicability in the textile, chemical, electronics, automobile manufacturing (Mirsanei et al., 2010; Zandieh et al., 2006), iron and steel (Pan et al., 2013), food processing, ceramic tile (Ruiz et al., 2008), packaging (Adler et al., 1993), pharmaceutical, and paper (Gholami et al., 2009) industries, among others.

The standard FS problem consists in m machines (resources) in series. There are n jobs (tasks) that have to be processed on every machine. All jobs must follow the same processing route on the shop floor; that is, jobs are performed initially on the first machine, next on the second machine, and so on, until machine m is reached. The decision to be taken is to determine the processing sequence of the n jobs on each machine. This results in a solution space of $n!^m$ (Pinedo, 2012). When the objective function is the makespan, the problem has been proved to be strongly NP-complete for three or more machines (Lee, Cheng, & Lin, 1993) and for the tardiness objective (Du et al., 2012). A generalization of the FS and parallel-machines environments is the FFS. In this case there are c stages, and at least one stage has two or more machines in parallel that process the same kind of operation. Thus, the decision to be made is which of the parallel machines each job should be allocated to at each stage. It can be seen that when there is only one machine in all stages then the problem is a standard FS one (Pinedo, 2012).

Most of the studies in FS and FFS scheduling have considered that all information is known, that is, deterministic. Nevertheless, within organizations, various parameters are not exactly known and vary over time, causing deterministic decisions to be inadequate. That is why scheduling under uncertainties is a very important issue that has received more attention from researchers in the last years (Elyasi & Salmasi, 2013a; Juan et al., 2014). Particularly in the area of stochastic flow shop (SFS), only one literature review has been published, in the year 2000 by (Gourgand et al., 2000a). Nevertheless, considering the growing and significance of this field it is important to update the state of the art and give some future directions for research.

This paper provides a general view of the developments in FS and FFS scheduling under uncertainties over the last 15 years and how these advances influence the research on production logistics. Section 2 describes the notation used for the literature review. Section 3 describes the different solution approaches presented in the literature and current state of research. Finally, several directions for future research are outlined in Section 4.

2. Notation

In order to present the literature review on FS and FFS problems under uncertainties we are going to follow the notation originally presented by Graham et al. (1979) and later adapted by Gourgand et al. (2000b) for stochastic static FS problems. In order to include (FFS) problems, we extend the notation presented by Gourgand et al. (2000b) since it was designed to classify stochastic FS problems only. We also adapted the notation to include unknown parameters modeled using both stochastic distribution and fuzzy sets. According to the notation in Graham et al. (1979), scheduling problems can be represented using three fields named $\alpha|\beta|\gamma$. The α field indicates the shop configurations. For the purpose of this review, two symbols are required: Fm (an FS with m machines) and FFc (an FFS with c stages). Field β denotes the special constraints and assumptions which differ from the standard problem of the specific shop. It includes uncertain parameters and the way in which they are modeled. Table 1 presents the basic notation of parameters (in the deterministic version) and characteristics of the shop problem. Depending on how the uncertain parameters are modeled, let us use the following conventions:

- When a parameter is modeled using a probability distribution we will denote it as $parameter{\sim}PF$, where PF is the probability function. For example, if the processing times of job j on machine i (p_{ij}) in an FS problem are modeled with a normal distribution with mean μ_{ij} and variance σ_{ij}^2, then its notation is $p_{ij}{\sim}Normal(\mu_{ij},\sigma_{ij}^2)$.
- When a general distribution is used, the parameter is denoted as $r_j{\sim}Gen$
- If the uncertain parameter is modeled as a fuzzy number, the notation becomes $Fuz(parameter)$, that is, $Fuz(p_{ij})$.
- If the parameter is not modeled with a distribution probability or as a fuzzy number but it can take random values in a specific interval, it is denoted as $L \leq Parameter \leq U$. For example, $L_j \leq d_j \leq U_j$ if the due date of job j varies between the values L_j and U_j.
- For inverse scheduling in which a controllable parameter is adjusted, we denote it as $adj(parameter)$.

Table 1
Notation used in $\boldsymbol{\beta}$ field

Type	Notation	Meaning
Parameters	d_j	Due date of job j
	p_{ij}	Processing time of job j on machine i (in an FS) or processing time of job j in stage i (in an FFS)
	r_j	Release date of job j
	s_{gh}	When a machine switches over from one job family to another, s_{gh} denotes the sequence-dependent setup times between family g and job family h
	s_{ij}	Sequence-independent setup time of job j on machine i
	s_{ijk}	Sequence-dependent setup time when job k is going to be processed just after job j on machine i
	t_{im}	Transportation time between machines i and m in an FS or between stages i and m in an FFS
	w_j	Weights of jobs
Special characteristics	R_m	Unrelated parallel machines in the case of FFS environments
	Ag	Breakdown level of the shop. Some researches uses this approach to define the time between failures (TBF) (Holthaus, 1999)
	BPM	Time taken for basic preventive maintenance
	MPM	Time taken for minimal preventive maintenance
	SZ_j	Size of job j. This characteristic can be used when a machine can process batches and jobs have different sizes
	$batch(b)$	Machines can process a batch of b jobs simultaneously
	$block$	When the buffer capacities between machines in an FS or between stages in an FFS are limited, the jobs must wait in the previous machine (FS) or stage (FFS), blocking it until sufficient space is released in the buffer.
	$brkdwn(a, b)$	Machine breakdowns. The information enclosed in parentheses is: a the time between failures (TBF) and b the time to repair (TTR).
	$dgrdtn$	Degradation of machines due to shocks. It means that machines have to be subject to preventive maintenance
	$dynarrv$	Dynamic arrivals.
	$fmls$	Families of jobs. When jobs of the same family or group are processed consecutively on the same machine, a setup time for each job is not needed.
	lot	Lot sizing
	$lotstrm$	Lot streaming
	nwt	No wait. Jobs are not allowed to wait between machines
	$prec$	Precedence. It can take place in parallel machines of a FFS, implying that a job can only be processed after all predecessors have been completed.
	$prmp$	Preemption. The processing of a job on a machine can be interrupted and finished later. Penalties may apply.
	$prmu$	Permutation. This only happens in FS and indicates that the execution sequence of jobs in all machines is the same.
	$rcrc$	Recirculation or reentrant: a job may visit a machine or a stage more than once.
	$splt$	Order splitting

Finally, field γ corresponds to the decision criteria or optimization objectives. In order to explain the possible objectives in the γ field, let us define:

- c_{ij}, the completion time of job j on machine i for FS or in stage i for an FFS problem
- C_j, the completion time of job j on the last machine in an FS or in the last stage in an FFS
- F_j, the flow time of job j, calculated as $F_j = C_j - r_j$
- L_j, the lateness of job j, calculated as $L_j = C_j - d_j$
- T_j, the tardiness of job j, calculated as $T_j = \max(C_j - d_j, 0)$
- E_j, the earliness of job j, calculated as $E_j = \max(d_j - C_j, 0)$
- $U_j = 1$ if the job j is tardy, that is, if $C_j - d_j > 0$, and 0 otherwise.

The possible objective functions (X) for the deterministic counterparts of scheduling problems are presented in Table 2. It is important to note that the γ field is extended to express one of the following ways to deal with uncertainty:

$$\gamma\ field \begin{cases} X_{w.p.1} & minimization\ with\ probability\ 1\ of\ criterion\ X \\ X_{st} & stochastic\ minimization\ of\ criterion\ X \\ E[X] & minimization\ of\ the\ expected\ value\ of\ criterion\ X \\ Rob(X) & robust\ schedule\ according\ to\ criterion\ X \\ Fuz(X) & schedule\ according\ to\ the\ fuzzy\ approach\ for\ criterion\ X \\ Intvl(X) & schedule\ according\ to\ the\ interval\ number\ approach\ for\ criterion\ X \end{cases}$$

Table 2
Objective functions in deterministic scheduling

Notation (X)	Formula	Meaning
$Cmax$	$\max_j C_j$	Makespan or maximum completion time
$Fmax$	$\max_j F_j$	Maximum flow time
$Lmax$	$\max_j L_j$	Maximum lateness
$Tmax$	$\max_j T_j$	Maximum tardiness
$\bar{C}$	$\sum_j C_j$	Total/average completion time
$\bar{C}^w$	$\sum_j w_j C_j$	Total/average weighted completion time
$\bar{F}$	$\sum_j F_j$	Total/average flow time
$\bar{F}^w$	$\sum_j w_j F_j$	Total/average weighted flow time
T	$\sum_j T_j$	Total tardiness
T^w	$\sum_j w_j T_j$	Total weighted tardiness
E	$\sum_j E_j$	Total earliness
E^w	$\sum_j w_j E_j$	Total weighted earliness
U	$\sum_j U_j$	Total number of tardy jobs
WIP		Work-in-process inventory
THR		Throughput time

The complete $\alpha|\beta|\gamma$ notation presented is illustrated using five examples:

- $F3|Fuz(p_{ij})|C_{max}$ corresponds to an FS environment with three machines in which the processing times are modeled using fuzzy numbers and the objective function is the makespan.

- $FFc|p_{ij}{\sim}Lognormal(\mu_{ij},\sigma_{ij})\ |E[\bar{C}],E[T]$ is an FFS with c stages in which the processing times follow a lognormal distribution with mean μ_{ij} and standard deviation σ_{ij}. The problem analyzes a bi-objective function that is solved through a Pareto approach. For this case, the objectives are the expected total completion time and the expected total tardiness.
- $FFc|brkdwn{\sim}(exp(\mu_s),Lognormal(\alpha_s,\beta_s))\ |F_{w\cdot p\cdot 1}$ is an FFS with c stages in which machine breakdowns are stochastic. The time between failures follows an exponential distribution with mean μ_s at each stage. The time to repair follows a lognormal distribution with mean α_s and standard deviation of β_s at stage s. The objective function is the minimization of the flow time with probability 1.
- $Fm|r_j|Fuz(\alpha\ C_{max}+\beta\ T)$ consists of an FS with m machines that considers deterministic release times. The objective function is to minimize the weighted sum of makespan and tardiness, but the weights for each function α and β are not known and are thus modeled as fuzzy numbers.
- $Fm|Range(d_j)|Rob(T_{max})$ corresponds to an FS environment with m machines in which the due dates are random variables that can vary in an interval. The objective is to construct a robust schedule according to a maximum tardiness criterion.

3. Literature review

As mentioned previously, FS and FFS under uncertainties have not been well studied as deterministic counterparts. Only one literature review presented by (Gourgand et al., 2000a) was found for the static version of the stochastic FS. Those authors noticed that the majority of researches considered that either processing times or breakdowns of machines were subject to uncertainties. In addition, that review revealed that the majority of the revised works analyzed the cases of FS with only two machines. Since then, this field has been growing and there are more complex applications nowadays. The nomenclature presented in the previous section was used to summarize the type of problem addressed in 100 papers published between 2001 and October 2016. The year 2001 was chosen as the starting point in time as it corresponds to the time immediately after the publication of the review in (Gourgand et al., 2000a).

According to Fink (1998) and Badger et al. (2000), from a methodological point of view, a literature review is a systematic, explicit, and reproducible approach for identifying, evaluating, and interpreting the existing body of documents. This paper follows the principles of systematic literature reviews, in contrast to narrative reviews, by being more explicit in the selection of the studies and employing rigorous and reproducible evaluation methods (Delbufalo, 2012; Thomé et al., 2016). A set of criteria was defined to collect and identify the research papers from the Science Citation Index compiled by Clarivate Analytics (formerly the Institute for Scientific Information, ISI) and SCOPUS databases. The inclusion and exclusion criteria are explained next:

- Inclusion criteria: Title–abstract–keywords (flowshop OR "flow shop" OR flowline) AND (random OR randomness OR stochastic OR uncertainty OR uncertainties OR robust OR robustness OR fuzzy) AND publication year > 2000
- Exclusion criteria:
    - Random elements are part of the solution method but not characteristics of the parameters. For example, all parameters and objective function are deterministic but the solution method is a random key genetic algorithm.
    - The article is not about scheduling. For example, the main topic of the paper is “subsea flowline buckle capacity considering uncertainty”.
    - The paper is written in a language other than English.
    - The paper was published in conference proceedings.

The list of reviewed papers is presented in Table 3. The first column of the table indicates the bibliographical reference (including the publication year), the second one describes the problem addressed in the paper with the proposed notation, and the third column briefly describes the type of solution approach and in some cases other details that may be of interest. This table follows a similar format to that presented in (Ruiz & Vázquez-Rodríguez, 2010). The fourth to sixth columns indicate which approach was used for modeling uncertain parameters. The seventh to eleventh columns indicate what kind of solution method was used to deal with uncertainty. Lastly, the twelfth to fourteenth columns show what kind of method was employed for optimization.

As illustrated in the table, there is a trend of an increase in the number of papers published on FS and FFS under uncertainties. This is helped by the existence of more rapid computers and advances that allow more complex problems to be solved. Fig. 1 shows the evolution of the number of papers separately for FS and FFS under uncertainties and the total values. There is a big difference between FS and FFS, with FFS representing 25% of the revised works.

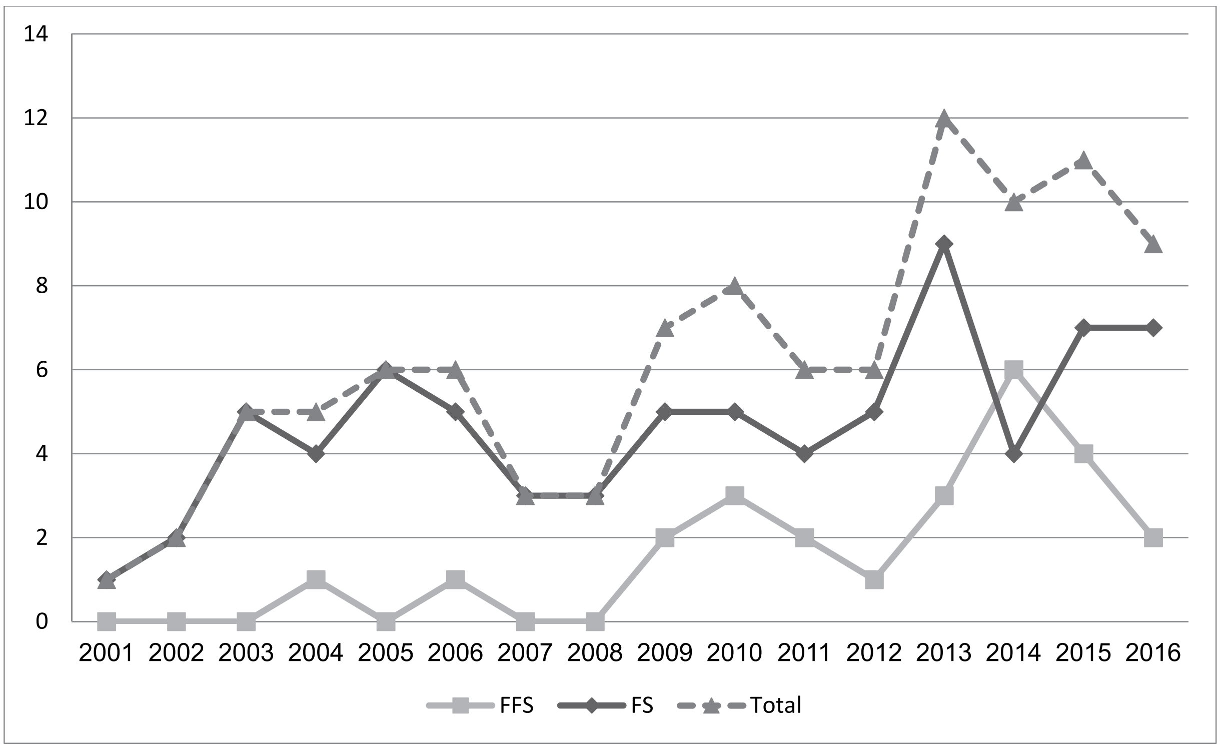

Fig. 1. Number of papers per year on FS and FFS under uncertainties

There are some issues to be highlighted from the literature, so the following subsections summarize the findings in terms of four characteristics:

- Uncertain parameters and methods to describe them (fuzzy, bounded, probability)
- Approach used to deal with uncertainty (fuzzy, robust, stochastic (not simulation), simulation-optimization and interval theory)
- Optimization methods
- Objective function

Table 3
Classification of the reviewed works

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Allahverdi & Savsar, 2001)	$Fm\|p_{ij}=p_j, s_{ij}=s_j, brkdwn(LTBF \le TBF \le UTBF, LTTR \le TTR \le UTTR)\|Cmax_{w.p.1}$	Dominance analysis		√				√			√		
(Alcaide et al., 2002)	$Fm\|p_{ij}\sim exp(\lambda_{ij}), brkdwn(exp(\lambda_{1i}), \quad exp(\lambda_{2i}))\|E[Cmax]$	Dynamic algorithm to convert a problem subject to breakdowns into a problem without breakdowns			√			√				√	
(Balasubramanian & Grossmann, 2002)	$Fm\|batch(b), p_{ij}\sim Discrete\ Uniform(\alpha,\beta)\|E[Cmax]$	Branch and bound			√			√			√		
(Allahverdi et al., 2003)	$F2\|L_{ij} \le s_{ij} \le U_{ij}\|Intvl(Cmax)$ $F2\|L_{ij} \le s_{ij} \le U_{ij}\|Intvl(\bar{C})$	Dominance analysis		√	√					√	√		
(Balasubramanian & Grossmann, 2003)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Fuzzy set theory with tabu search	√			√							√
(Celano et al. , 2003)	$Fm\|Fuz(p_{ij}), Fuz(d_j)\|Fuz(Cmax,T)$	Genetic algorithm	√			√							√
(Chutima & Yiangkamolsing, 2003)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Fuzzy genetic algorithm	√			√							√
(Gourgand et al., 2003)	$F3\|prmu, p_{ij}\sim exp(\lambda_{ij})\|E[Cmax]$	Markov optimization and simulation-optimization with simulated annealing. The Markov chain approach presents lower computational times in small instances, while the simulation approach is recommended for larger instances with makespan minimization.			√				√		√		√
(Allahverdi, 2004)	$F3\|brkdwn(LTBF \le TBF \le UTBF, LTTR \le TTR \le UTTR)\|Cmax_{st}$	Dominance analysis. Optimal solutions are obtained when certain conditions are satisfied.		√				√		√	√		
(Kalczynski & Kamburowski, 2004)	$F2\|p_{ij}\sim Gompertz(\lambda_{ij},\gamma_{ij})\|Cmax_{st}$	New scheduling rule that generalizes Johnson's and Talwar's rules			√			√				√	
(Sotskov et al., 2004)	$F2\|L_{ij} \le p_{ij} \le U_{ij}\|Intvl(\bar{C})$ $F3\|L_{ij} \le p_{ij} \le U_{ij}\|Intvl(\bar{C})$	Dominance analysis		√						√	√		
(Temİz & Erol, 2004)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Fuzzy branch and bound	√			√					√		

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters: Fuzzy	Modeling of uncertain parameters: Bounded	Modeling of uncertain parameters: Probability	Approach taken to deal with uncertainty: Fuzzy	Approach taken to deal with uncertainty: Robust	Approach taken to deal with uncertainty: Stochastic (not simulation)	Approach taken to deal with uncertainty: Simulation-optimization	Approach taken to deal with uncertainty: Interval theory	Optimization method: Exact	Optimization method: Heuristic	Optimization method: Metaheuristic
(Yang et al., 2004)	$FFc\|batch(b), s_{ij}\sim Uniform(\alpha_i,\beta_i),\quad brkdwn(exp(\lambda_{1i}), exp(\lambda_{2i}))\|E[T]$	Simulation-optimization with tabu search			√				√				√
(Gourgand et al., 2005)	$Fm\|block, p_{ij}\sim exp(\lambda_{ij})\|E[Cmax]$ $Fm\|p_{ij}\sim exp(\lambda_{ij})\|E[Cmax]$	A theorem that provides a recursive scheme based on Markov chains and Chapman–Kolmogorov equations to compute the expected makespan. This scheme is combined with simulated annealing.			√			√			√		√
(Hong & Chuang, 2005)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Fuzzy Gupta algorithm	√			√							
(Pawel Jan Kalczynski & Kamburowski, 2005)	$F2\|block, p_{ij}\sim exp(\lambda_{ij})\|Cmax_{st}$	Assuming that the job processing times can be stochastically ordered on both machines, the authors show that the problem is equivalent to traveling salesman problem on a permuted Monge matrix and prove its NP-hardness			√			√			√		
(Soroush & Allahverdi, 2005)	$F2\|p_{ij}\sim Normal(\mu_{ij},\sigma_{ij}^2)\|E[\bar{C}]$	Exact approaches			√			√			√		
(Wang et al., 2005a)	$Fm\|p_{ij}\sim Uniform(\alpha_{ij},\beta_{ij})\|E[Cmax]$	Hypothesis-test method incorporated into a genetic algorithm			√				√				√
(Wang et al., 2005b)	$Fm\|p_{ij}\sim Uniform(\alpha_{ij},\beta_{ij})\|E[Cmax]$	Simulation-optimization approach that hybridizes ordinal optimization, optimal computing budget allocation and a genetic algorithm			√				√				√
(Allahverdi, 2006)	$F2\|LS_{ijk}\le s_{ijk}\le US_{ijk}, L_{ij}\le p_{ij}\le U_{ij}\|Intvl(\bar{C})$	Development of two dominance relations to obtain the set of dominant schedules		√						√	√		
(Averbakh, 2006)	$F2\|prmu, L_{ij}\le p_{ij}\le U_{ij}\|Intvl(Cmax)$	Interval data min-max regret. Linear-time algorithm based on the geometric formulation of the problem without uncertainty		√						√			
(Azaron et al., 2006)	$Fm\|dynarrv, p_{ij}\sim exp(\lambda_{1ij}), t_{im}\sim exp(\lambda_{1im})\|E[\bar{F}]$	Method for approximating the distribution function of the longest path length in the network of queues by constructing a proper continuous-time Markov chain			√			√					
(Pawel Jan Kalczynski & Kamburowski, 2006)	$F2\|p_{ij}\sim Weibull(\alpha_{ij},\beta_{ij})\|Cmax_{st}$	The same coefficient of variation for all processing times. Extension of Johnson's and Talwar's rules.			√			√			√		
(Petrovic & Song, 2006)	$F2\|Fuz(p_{ij})\|Fuz(Cmax)$	Algorithm based on the Johnson algorithm and a modification of McCahon and Lee's approach.	√			√						√	

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Schultmann et al., 2006)	$FFc\|Fuz(s_{ijk}), Fuz(p_{ij}), prec, batch(b)\|\alpha\, THR + \beta\, Cmax + \gamma\, T$	Fuzzy approach that delivers six schedules for the crisp problems. Although the six schedules are most probably not identical, the decision-maker receives optimal and good solutions for different membership levels	√			√							
(Alfieri, 2007)	$Fm\left\|dynarrv, brkdwn\left(exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\frac{(1-Ag)}{Ag}\right), \quad exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\right)\right)\right\|E[Tmax]$	Simulation-optimization approach with dispatching rules			√			√				√	
(Chen & Shen, 2007)	$Fm\|dynarrv, LR_j \leq r_j \leq UR_j, L_{ij} \leq p_{ij} \leq U_{ij}, LW_j \leq w_j \leq UW_j\|\bar{C}^w_{w.p.1}$	Probabilistic asymptotic analysis of the problem, finding good results for two different non-delay algorithms		√				√			√		
(Swaminathan et al., 2007)	$Fm\left\|dynarrv, p_{ij}{\sim}Triangular\left(\mu_{ij}(1-f), \mu_{ij}, \mu_{ij}(1+f)\right)\right\|E[T^w]$	Simulation-optimization with dispatching rules and genetic algorithms. The approaches studied are categorized as follows: pure permutation scheduling, shift-based scheduling, and pure dispatching for non-permutation sequences.			√				√			√	√
(Javadi et al., 2008)	$Fm\|prmu, nwt\|Fuz(\bar{C}^w, E^w)$	Fuzzy multi-objective linear programming model. Fuzzification of the aspiration levels of the objectives.	√			√					√		
(Nezhad & Assadi, 2008)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Method that approximates the maximum operator as a triangular fuzzy number with CDS algorithm	√			√						√	
(Niu & Gu, 2008)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Particle swarm optimization	√			√							√
(Gholami et al., 2009)	$FFc\left\|s_{ijk}, brkdwn\left(exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\frac{(1-Ag)}{Ag}\right), exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\right)\right)\right\|E[Cmax]$	Simulation-optimization approach with genetic algorithm			√				√				√
(Matsveichuk et al., 2009)	$F2\|\,L_{ij} \leq p_{ij} \leq U_{ij}\|Cmax_{st}$	Two phases: off-line and on-line scheduling. This set of dominant schedules allows an on-line scheduling decision to be made whenever additional local information on the realization of an uncertain processing time is available. Dominance.			√				√				√
(Ng et al., 2009)	$F2\|\,L_{ij} \leq p_{ij} \leq U_{ij}\|Intvl(Cmax)$	Dominance relation. Mathematical approach.			√				√				√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Safari et al., 2009)	$Fm\|drgdtn, MPM\sim Lognormal(\mu,\sigma^2), \quad BPM\sim Lognormal(\mu,\sigma^2)\|E[Cmax]$	Simulation-optimization approach with NEH heuristic, simulated annealing, and the genetic algorithm separately. Results show the superiority of the genetic algorithm.	√								√		√
(Sancar Edis & Ornek, 2009)	$Fm\|lotstrm, p_{ij}\sim Normal(\mu_{ij}=E[p_{ij}], \sigma_{ij}^2=k^2p_{ij}^2)\|E[Cmax]$	Simulation-optimization with tabu search		√						√	√		
(Yimer & Demirli, 2009)	$Fm\|fmls, Fuz(s_{gh}), Fuz(p_{ij})\|Fuz(\bar{F})$	Mixed-integer fuzzy programming model and a genetic algorithm solution approach			√				√				√
(Zandieh & Gholami, 2009)	$FFc\left\|s_{ijk}, brkdwn\left(exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\frac{(1-Ag)}{Ag}\right), exp\left(k\frac{\sum_j p_{ij}}{\|J\|}\right)\right)\right\|E[Cmax]$	Simulation-optimization approach with an immune algorithm		√				√			√		
(Allahverdi & Aydilek, 2010b)	$F2\|L_{ij}\le p_{ij}\le U_{ij}\|Intvl(Lmax)$	Fourteen heuristics		√						√		√	
(Allahverdi & Aydilek, 2010a)	$F2\|L_{ij}\le p_{ij}\le U_{ij}\|Intvl(Cmax)$	Five heuristics		√						√		√	
(Aydilek & Allahverdi, 2010)	$F2\|L_{ij}\le p_{ij}\le U_{ij}\|Intvl(\bar{C})$	Eleven heuristics based on SPT rule		√						√		√	
(Azadeh et al., 2010)	$FFc\|Fuz(s_{ijk}), Fuz(brkdwn)\|Rob(Cmax)$	Flexible artificial neural network–fuzzy simulation algorithm with dispatching rules	√			√	√		√				√
(Diep et al., 2010)	$F2\|brkdwn(Uptime\sim Lognormal(\mu,\sigma), Downtime\sim Weibull(\alpha,\beta))\|E[Cost\ of\ inventory]$	Dynamic programming and a semi-Markov process.			√			√			√		
(Geismar & Pinedo, 2010)	$Fm, robotic\ cell\ one\ robot\|p_{robot}\sim Gen\|E[THR]$	Common environment in the microlithography portion of semiconductor manufacturing. The objective is to maximize throughput quantities, which is equivalent to minimizing the throughput times. Markov chains.			√			√			√		
(Paul & Azeem, 2010)	$FFc\|w_j^{Fuz}\|Fuz(WIP)$	Fuzzy due dates, cost over time, and profit rate, resulting in job priority. Grouping and sequencing algorithm.	√			√							
(Wang & Choi, 2010)	$FFc\|p_{ij}\sim Gamma(\mu_{ij}=E[p_{ij}], \sigma=CV*E[p_{ij}])\|E[Cmax]$	Decomposition-based approach to decompose the problem into several machine clusters. A neighboring K-means clustering algorithm is designed to group machines in clusters. Then a genetic algorithm or SPT rule generates the schedule for each machine cluster.			√				√				√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Baker & Trietsch, 2011)	$F2 \mid p_{ij} \sim Exp(\lambda_{ij}) \mid E[Cmax]$ $F2 \mid p_{ij} \sim Uniform(\alpha_{ij}, \beta_{ij}) \mid E[Cmax]$ $F2 \mid p_{ij} \sim Lognormal(\mu_{ij}, \sigma_{ij}^2) \mid E[Cmax]$	Three different heuristic procedures			√			√				√	
(Chaari et al., 2011)	$FFc \mid p_{ij} \sim Uniform(\alpha_j, \beta_j) \mid Rob(Cmax)$	Genetic algorithm			√		√						√
(Jiao et al., 2011)	$Fm \mid Fuz(p_{ij}) \mid Fuz(Cmax)$	Maximum membership function of mean value is applied to convert the fuzzy optimization problem into a general optimization problem. The optimization problem is solved with a cooperative co-evolutionary particle swarm optimization algorithm.	√			√							√
(Liu et al., 2011)	$Fm \mid p_{ij} \sim Normal(\mu_{ij}, \sigma_{ij}^2) \mid Rob(Cmax)$	Improved genetic algorithm with a new generation scheme, which can preserve good characteristics of parents in the new generations. Robustness is achieved by maximizing $Prob(Cmax < E[\bar{C}])$			√		√						√
(Matsveichuk et al., 2011)	$F2 \mid L_{ij} \leq p_{ij} \leq U_{ij} \mid Intvl(Cmax)$	Dominance digraph		√						√	√		
(Wang & Choi, 2011)	$FFc \mid brkdwn(Exp(\lambda_{1i}), Exp(\lambda_{2i})) \mid E[Cmax]$	Decomposition-based approach to decompose the problem into several cluster scheduling problems. A neighboring K-means clustering algorithm is designed to group machines in clusters. Then a genetic algorithm or SPT rule generates the schedule for each machine cluster.			√				√				√
(Azadeh et al., 2012)	$Fm \mid prmu, s_{ij}, p_{ij} \sim Normal(\mu_{ij}, \sigma_{ij}^2), brkdwn(exp(\lambda_{1i}), exp(\lambda_{2i})) \mid E[\alpha\, Cmax + (1-\alpha)\bar{C}]$ $F2 \mid prmu, s_{ij}, p_{ij} \sim Normal(\mu_{ij}, \sigma_{ij}^2), brkdwn(Weibull(\alpha_i), Weibull(\beta_i)) \mid E[\alpha\, Cmax + (1-\alpha)\bar{C}]$	Integrated computer simulation and artificial neural network algorithm			√				√				√
(Baker & Altheimer, 2012)	$Fm \mid p_{ij} \sim Exp(\lambda_{ij}) \mid E[Cmax]$ $Fm \mid p_{ij} \sim Uniform(\alpha_{ij}, \beta_{ij}) \mid E[Cmax]$ $Fm \mid p_{ij} \sim Lognormal(\mu_{ij}, \sigma_{ij}^2) \mid E[Cmax]$	Simulation-optimization approach with three constructive procedures based on approaches that have been successful for solving the deterministic counterpart.			√				√			√	
(Choi & Wang, 2012)	$FFc \mid p_{ij} \sim Gamma(\mu_{ij} = E[p_{ij}], \sigma = CV * E[p_{ij}]) \mid E[Cmax]$	Novel decomposition-based approach combining both SPT and a genetic algorithm. Simulation for evaluating results.			√				√				√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Huang et al., 2012)	$Fm\|Fuz(p_{ij}), Fuz(d_j)\|Fuz(\alpha\ E + \beta\ T)$	Longest common substring method combined with the random key method. The algorithm is enhanced for solving large-sized problems using nVidia's parallel computing architecture.	√			√							√
(Kasperski et al., 2012)	$F2\|L_{ij} \leq p_{ij} \leq U_{ij}\|Rob(Cmax)$	Min-max and min-max regret criteria were selected. The uncertainty of processing times is modeled through scenario sets.		√			√						
(Liefooghe et al., 2012)	$F2\|prmu, p_{ij}{\sim}Uniform(\alpha_{ij}, \beta_{ij})\|Rob(Cmax, T)$ $F2\|prmu, p_{ij}{\sim}Exp(\lambda_{ij})\|Rob(Cmax, T)$ $F2\|prmu, p_{ij}{\sim}Normal(\mu_{ij}, \sigma_{ij}^2)\|Rob(Cmax, T)$ $F2\|prmu, p_{ij}{\sim}Lognormal(\mu_{ij}, \sigma_{ij}^2)\|Rob(Cmax, T)$	Simulation-optimization with indicator-based evolutionary algorithm to handle both multiple objectives and uncertain environment simultaneously			√		√		√				√
(Almeder & Hartl, 2013)	$FFc\|blocking, p_{ij}{\sim}Uniform(\alpha, \beta)\|E[0.5X_1 + 0.25X_2 + 0.25Cmax]$ X_1: utilization of machine 1 X_2: utilization of the buffer	Real application in a metal-working industry. Variable neighborhood search			√				√				√
(Aydilek & Allahverdi, 2013)	$F2\|s_{ij}, L_{ij} \leq p_{ij} \leq U_{ij}\|Cmax$	Polynomial time heuristic algorithm. Both the Johnson algorithm and the Yoshida and Hitomi algorithm, developed for the deterministic counterpart of the problem, are special cases of the proposed algorithm.		√						√		√	
(Aydilek et al., 2013)	$F2\|\ L_{ij} \leq s_{ij} \leq U_{ij}\|Intvl(Cmax)$	Polynomial time algorithm that generalizes Yoshida and Hitomi's algorithm			√					√		√	
(Bayat et al., 2013)	$F2\|dynarrv, prmp, p_{ij}{\sim}Normal(\mu_{ij}, \sigma_{ij})\|E[Cmax]$	Heuristic algorithm			√			√				√	
(Elyasi & Salmasi, 2013a)	$Fm\|r_j, d_j{\sim}Normal(\mu_j, \sigma_j)\|E[U]$	Dynamic method that decomposes the problem into m subproblems, one for each machine. Each single machine sub-problem is solved through a mathematical programming model.			√			√			√		
(Elyasi & Salmasi, 2013b)	$F2\|p_{ij}{\sim}Normal(\mu_{ij}, \sigma_{ij}^2), d_j = d\|U_{st}$ $F2\|p_{ij}{\sim}Gamma(\alpha_j, \beta_j), d_j = d\|U_{st}$	Chance-constrained programming			√			√			√		
(Gören & Pierreval, 2013)	$FFc\|brkdwn(Gen, Gen)\|Cmax, Rob(Cmax)$	New two-step framework. The first phase generates different schedules using a multimodal optimization approach. In the second phase, the decision-maker can select the alternatives according to other criteria not considered in the first phase. Genetic algorithm for multimodal optimization to minimize Cmax. In the second phase, the idea is to select a robust schedule under machine breakdowns.			√		√		√				√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Heydari et al., 2013)	$F2\|p_{ij}\sim Normal(\mu_{ij},\sigma_{ij}^2)\|E[Cmax]$	Mathematical method that uses the properties of the normal distribution.			√			√			√		
(Katragjini et al., 2013)	$Fm\|dynarrv, prmu, r_j\sim Uniform(\alpha_1,\beta_1), brkdwn(Uniform(\alpha_2,\beta_2), Uniform(\alpha_2,\beta_2))\|E[U]$	Predictive-reactive approach consisting of two steps: generation and control. The first step solves the deterministic problem with an iterative greedy algorithm. The second phase is reactive: it updates the prior schedule in response to unexpected disruptions.			√				√				√
(Nakhaeinejad & Nahavandi, 2013)	$Fm\|Fuz(p_{ij})\|Cmax, \bar{F}, machine\ idle\ time$	Integration between technique for order preference by similarity to an ideal solution and interactive resolution method to obtain non-dominated solutions	√			√							
(Ramezanian & Saidi-Mehrabad, 2013)	$Fm\|s_{ijk}, lot, p_{ij}\sim Normal(\mu_{ij},\sigma_{ij}^2)\|(Cost\ of\ production\ system)_{st}$	Chance-constrained programming for transforming the stochastic problem into a deterministic one. Hybrid simulated annealing and Mixed Integer Programming-based heuristics. Total cost of production system includes costs of production, holding, backorder, and setup-time costs.			√			√					√
(Kai Wang et al., 2013)	$FFc\|brkdwn(exp(\lambda_1), exp(\lambda_2)), p_{ij}\sim Gamma(\mu_{ij}=E[p_{ij}], \sigma = CV * E[p_{ij}])\|E[Cmax]$	Cluster-based scheduling model that combines the features of the SPT rule and simulated annealing.			√				√				√
(Behnamian & Fatemi Ghomi, 2014)	$FFc\|Fuz(s_{ijk}), Fuz(p_{ij})\|Fuz(Cmax, E+T)$	Bi-level algorithm. The authors obtain the Pareto front. First level: the population is decomposed into parallel sub-populations and solved with a random key genetic algorithm. In the second level, non-dominant solutions obtained in the first level are unified. Then, particle swarm optimization is used to improve the Pareto front.	√			√							√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Chang & Huang, 2014)	$Fm\|rcrc, brkdwn(\exp(\mu_1), \exp(\mu_2))\|U, T, L, WIP, F$	Enhanced simplified drum-buffer-rope model to compare three approaches: due-date assignment, dispatching rule, and release rule.			√			√				√	
(Cui & Gu, 2014)	$FFc\|brkdwn(Normal(\mu_1, \sigma_1), Normal(\mu_2, \sigma_2))\|Cmax$	Discrete group search optimizer algorithm. The paper considers two cases after a machine breakdown occurs: the job continues and the job must be repeated. Simulation for comparisons			√			√					√
(Ebrahimi et al., 2014)	$FFc\|s_{ijk}, d_j \sim Normal(\mu_j, \sigma_j)\|Cmax, T_{st}$	Two metaheuristic algorithms based on the genetic algorithm: non-dominated sorting genetic algorithm and multi objective genetic algorithm			√			√					√
(Jiao & Yan, 2014)	$Fm\|Fuz(p_{ij})\|Fuz(Cmax)$	Cooperative co-evolutionary particle swarm optimization algorithm based on a niche-sharing scheme	√			√							√
(Juan et al., 2014)	$Fm\|prmu, p_{ij} \sim Lognormal(E[P_{ij}], \sigma_{ij} = k * E[P_{ij}])\|E[Cmax]$	Simheuristic (simulation-optimization) with an iterated greedy algorithm. k is a constant varying from 0.1 to 2.			√				√				√
(Rahmani & Heydari, 2014)	$FFc\|dynarrv, p_{ij} \sim Uniform(\alpha, \beta)\|Rob(Cmax)$	Proactive–reactive approach. The proactive phase uses robust optimization. The reactive one deals with the dynamic arrivals and minimizes the deterministic makespan given the original robust schedule of the first phase.			√		√						
(Rahmani et al., 2014)	$F2\|p_{ij} \sim Normal(E[P_{ij}], \sigma_{ij} = CV * E[P_{ij}])\|(\alpha_1^{Fuz} Cmax + \alpha_2^{Fuz} \bar{F} + \alpha_3^{Fuz} T)_{st}$	Chance-constrained programming, fuzzy goal programming, and genetic algorithm	√		√	√		√					√
(Wang & Choi, 2014)	$FFc\|p_{ij} \sim Gamma(E[P_{ij}], \sigma_{ij} = CV * E[P_{ij}])\|Cmax$	Decomposition-based holonic approach with a genetic algorithm			√			√					√
(Wang et al., 2014)	$FFc\|p_{ij} \sim Normal(E[P_{ij}], \sigma_{ij} = CV * E[P_{ij}])\|E[Cmax]$	Two-phase simulation-based estimation of distribution algorithm			√				√				√
(Aydilek et al., 2015)	$F2\|LS_{ij} \le s_{ij} \le US_{ij}, L_{ij} \le p_{ij} \le U_{ij}\|Cmax_{st}$	Dominance relation, polynomial time algorithm		√				√			√		

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters			Approach taken to deal with uncertainty					Optimization method		
			Fuzzy	Bounded	Probability	Fuzzy	Robust	Stochastic (not simulation)	Simulation-optimization	Interval theory	Exact	Heuristic	Metaheuristic
(Ćwik & Józefczyk, 2015)	$Fm\|prmu, L_{ij} \le p_{ij} \le U_{ij}\|Rob(Cmax)$	Minmax regret with an evolutionary heuristic		√						√			√
(Framinan & Perez-Gonzalez, 2015)	$Fm\|p_{ij} \sim Lognormal(\mu_{ij}, CV * \mu_{ij})\|E[Cmax]$	CV: coefficient of variation, new NEH-based heuristics			√				√			√	
(Lin & Chen, 2015)	$FFc\|R_m, s_{ijk}, prmp, p_{ij} \sim Empirical\ distributions\|E[\bar{F}], E[Fmax]$	Real application in a semiconductor back-end assembly facility. Simulation-optimization approach (genetic algorithm and optimal computing budget allocation). The probability distributions of processing times are not specified			√				√				√
(Mou et al., 2015)	$Fm\|prmu, adj(p_{ij})\|H + (\Delta C + \Delta P)$ H: Hamming distance, ΔC: adjustment of total completion times, ΔP: adjustment of processing times.	Inverse scheduling, multi-objective evolutionary algorithm											√
(Nagasawa et al., 2015)	$Fm\|prmu, L_{ij} \le p_{ij} \le U_{ij}\|Rob(\alpha\ PeakPower + (1-\alpha)\ Inventory)$	Robust production scheduling model that considers random processing times and the peak power consumption.		√					√				
(Noroozi & Mokhtari, 2015)	$Fm\|batch(b), p_{ij} \sim Uniform(\alpha, \beta)\|E[Cmax]$	Practical application of printed circuit boards assembly line Simulation-optimization (Monte Carlo + genetic algorithm)			√				√				√
(Qin et al., 2015)	$FFc, R_m\|dynarrv, s_{ijk}, p_{ij} \sim Erlang(k, \lambda)\|E[Cmax]$	Rescheduling, ant colony optimization			√			√					√
(Wang et al., 2015)	$FFc\|p_{ij} \sim Uniform(\alpha, \beta)\|Rob(Cmax)$	Order-based estimation of distribution algorithm. Robustness with $\lambda\ Cmax + (1-\lambda)\ SD[Cmax]$			√		√		√				√
(Ying, 2015)	$F2\|L_{ij} \le p_{ij} \le U_{ij}\|Rob(Cmax)$	Simulated annealing and iterated greedy algorithms separately. The Iterated greedy approach is more effective in small instances while simulated annealing is more effective in large instances.		√			√						√
(Zandieh & Hashemi, 2015)	$FFc\|brkdwn(exp(\lambda_1), exp(\lambda_2))\|E[\bar{C}]$	Simulation-optimization approach with genetic algorithm			√				√				√
(Adressi et al., 2016)	$Fm\|fmls, nwt, brkdwn(Weibull(\alpha_i, \beta_i), \quad k)\|E[Cmax]$	Genetic algorithm and simulated annealing separately			√			√					√
(Fazayeli et al., 2016)	$Fm\|brkdwn(exp(\lambda_{1i}), exp(\lambda_{2i}))\|Rob(Cmax)$	β-robustness criterion. The objective is $max[probability(Cmax <= X)]$ Simulation-optimization approach with a hybridization of genetic algorithm and simulated annealing			√		√		√				√

Table 3
Classification of the reviewed works (Continued)

Reference	Problem	Solution approach	Modeling of uncertain parameters: Fuzzy	Modeling of uncertain parameters: Bounded	Modeling of uncertain parameters: Probability	Approach taken to deal with uncertainty: Fuzzy	Approach taken to deal with uncertainty: Robust	Approach taken to deal with uncertainty: Stochastic (not simulation)	Approach taken to deal with uncertainty: Simulation-optimization	Approach taken to deal with uncertainty: Interval theory	Optimization method: Exact	Optimization method: Heuristic	Optimization method: Metaheuristic
(Feng et al., 2016)	$FF2\| L_{ij} \leq p_{ij} \leq U_{ij}\|Rob(Cmax)$	Robust min-max regret scheduling model. Firstly the authors derive some properties of the worst-case scenario for a given schedule. Then, both exact and heuristic algorithms are proposed.		√			√				√	√	
(Geng et al., 2016)	$Fm\|Fuz(p_{ij})\|Fuz(E^w + T^w)$	By using the method of maximizing the membership function of the middle value, a fuzzy scheduling model is transformed into a deterministic one. Then, a scatter search based particle swarm optimization algorithm is proposed.	√			√							√
(Gholami-Zanjani et al., 2016)	$Fm\| LS_{ijk} \leq s_{ijk} \leq US_{ijk}, L_{ij} \leq p_{ij} \leq U_{ij}\|Rob(Cmax)$ $Fm\|Fuz(s_{ijk}), Fuz(p_{ij})\|Fuz(Cmax)$	First, a deterministic mixed-integer linear programming model is presented for the deterministic problem. Then, the robust counterpart of the proposed model is solved. Finally, the fuzzy flow shop model is analyzed. The authors compare three approaches.	√			√							
(González-Neira et al., 2016)	$FFc\|p_{ij}{\sim}Uniform(\alpha_{ij}, \beta_{ij})\|Rob(T^w), Importance\ of\ customers$	Simulation-optimization with GRASP metaheuristic for the quantitative phase and the integral analysis method for qualitative and integral analysis.			√		√		√				√
(Han et al., 2016)	$Fm\|lot, block, L_{ij} \leq p_{ij} \leq U_{ij}\|Intvl(Cmax)$	Evolutionary multi-objective algorithm. Firstly, the method calculates the objective interval based on interval processing times. Then it converts the objective interval into a deterministic value with dynamical weights.		√						√			√
(Shahnaghi et al., 2016)	$Fm\|batch(b), L_{ij} \leq p_{ij} \leq U_{ij}, LZ_j \leq SZ_j \leq UZ_j\|Rob(Cmax)$	Particle swarm optimization with Bertsimas and Ben-Tal robust models		√			√		√				√
(Kai Wang, Huang, & Qin, 2016)	$Distributed\ Fm\|prmu, brkdwn(exp(\lambda_{1i}), exp(\lambda_{2i}))\|E[Cmax]$	Fuzzy logic-based hybrid estimation of distribution algorithm			√				√				√

3.1. Uncertain parameters and methods to describe them

According to Li and Ierapetritou (2008), in scheduling under uncertainties, several methods have been used to describe the uncertain parameters: bounded form, probability description, and fuzzy description. The bounded or interval form is when there is insufficient information to describe the data with a probability function but information about the lower and upper bounds in which the parameter can vary exists. In the probabilistic approach, the uncertainties are modeled with a probability distribution function. This method is used when there is enough information (historical data) to estimate these probabilities. Finally, fuzzy sets are also useful when there is no available historical data to determine the probability distribution. Fig. 2 presents the distribution of reviewed papers according to the ways in which uncertain parameters are modeled. A probability distribution is the most frequently used approach to model uncertainties. It is very practical in situations where organizations have sufficient information to estimate the distribution functions of the parameter.

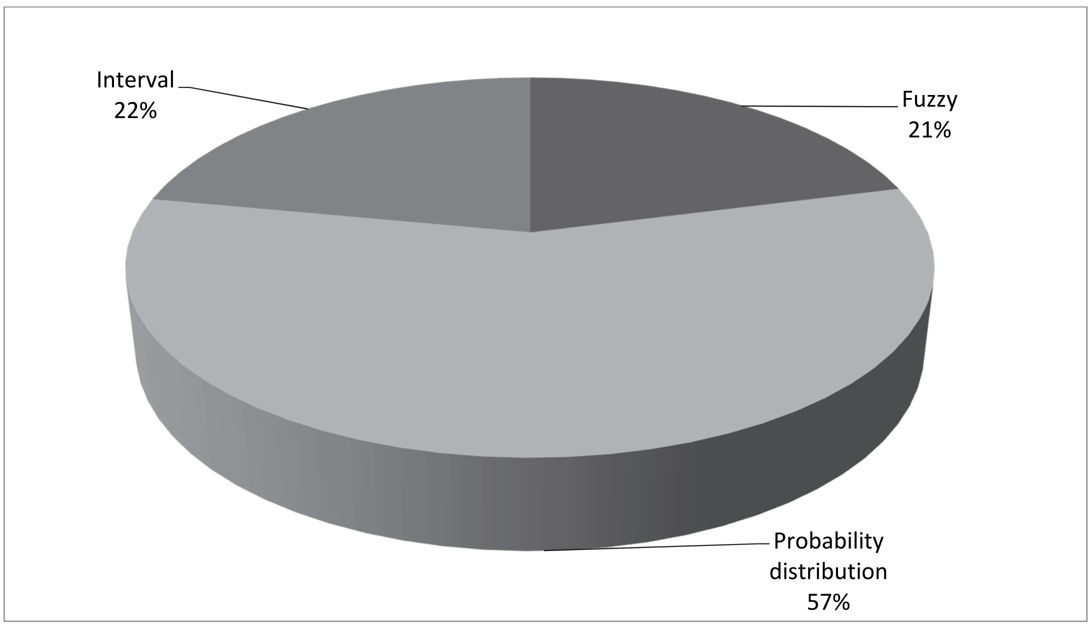

Fig. 2. *Distribution of methods for modeling uncertain parameters*

Fig. 3 presents the distribution of the parameters under uncertainty. It can be seen that 79% of the analyzed papers deal with only one stochastic parameter, 19% deal with two parameters, and only 2% deal with three parameters. The processing times are the most frequently studied parameter subject to uncertainty, representing 74% of shortlisted works, while the second most frequently used parameter is the breakdowns. Nevertheless, the consideration of breakdowns is still far from the use of processing times.

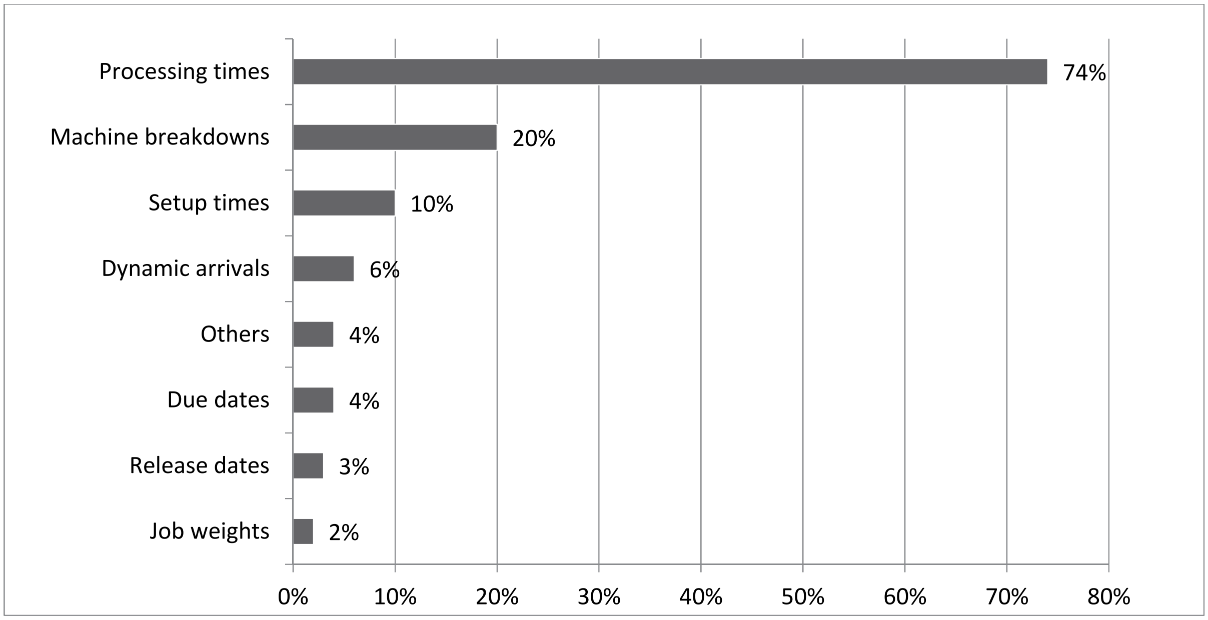

Fig. 3. Distribution of parameters under uncertainty

3.2 Approach to deal with uncertainty

Many approaches exist to deal with uncertain data: sensitivity analysis, fuzzy logic, stochastic optimization, and robust optimization (Behnamian, 2016; Elyasi & Salmasi, 2013a; Li & Ierapetritou, 2008). Sensitivity analysis is used to determine how a given model result can change with changes in the input parameters. This method has not been used much in scheduling due to the complex nature of this problem, which makes it impractical. The fuzzy programming method consists in the uncertain parameters being modeled as fuzzy numbers and constraints being modeled as fuzzy sets. In stochastic scheduling, discrete or continuous probability distributions are used to model random parameters. This approach is divided into three categories: two-stage or multi-stage stochastic programming, chance constraint programing, and simulation-optimization. Finally, robust optimization focuses on obtaining preventive schedules that minimize the effects of disruptions so the initial schedule does not change drastically after the disruption. Another approach to deal with uncertainty is the use of interval number theory, which is directly related with the representation of uncertain parameters through a bounded form. Interval number theory, or interval arithmetic, was pioneered by (Moore & Bierbaum, 1979). This method was originally used for bounding and rounding errors in computer programs. Since then, it has been generalized in order to extended its applications for dealing with numerical uncertainty in other fields (Lei, 2012).

Fig. 4 shows the approaches used in the reviewed literature. The stochastic approach has been employed the most, representing 60% of papers. It is important to note that among the papers using the stochastic approach, half used the simulation-optimization method, which has shown very good results in comparison with other methods. We highlight that few papers (9%) used a combination of two approaches.

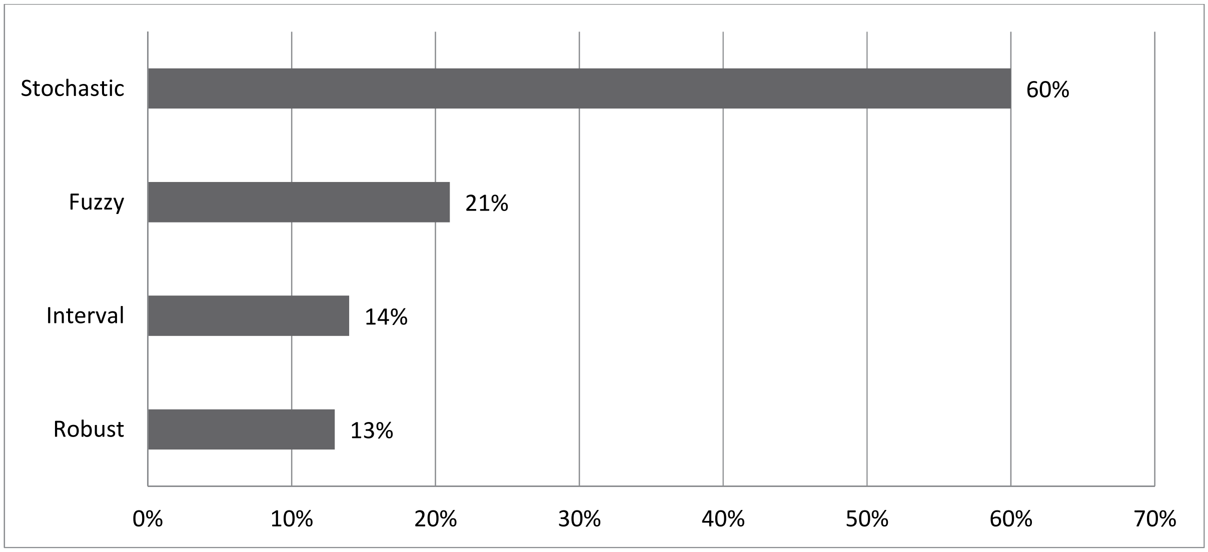

Fig. 4. Distribution of solution approach to deal with uncertainty

3.3.Optimization methods

Looking closer at the optimization approach to deal with these complex problems, 25% of reviewed papers employed exact approaches such as dominance analysis, Markov chains, mixed-integer linear programming, fuzzy linear programming models, and chance-constraint programming. Heuristic algorithms, including dispatching rules and more sophisticated heuristics, were applied in 17% of the works. Finally, 53% of articles used metaheuristics, with genetic algorithms, which were used in 24% of the total reviewed papers, standing out. Fig. 5 shows the distribution of metaheuristics among the 53 papers that implemented them as part of the solution approach.

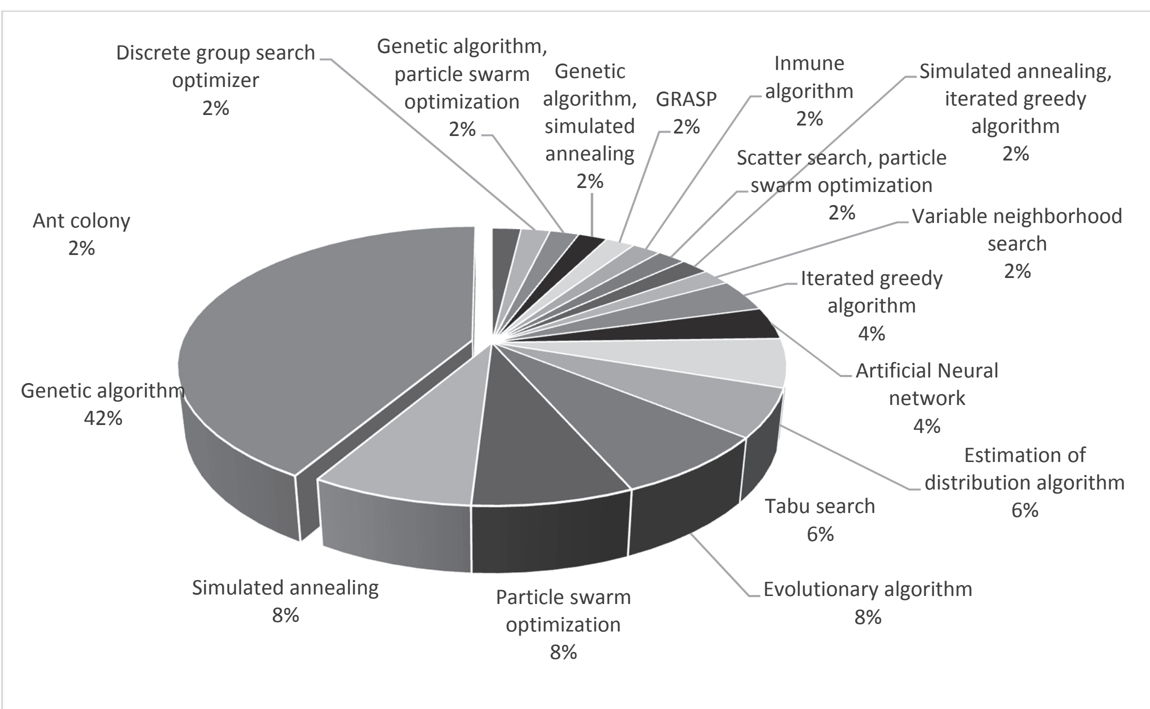

Fig. 5. Distribution of metaheuristics

3.4 Objective functions (decision criteria)

Most (81%) of the reviewed works deal with a single objective, 8% considers two objectives, and the others deal with three objective functions. Makespan, as in many other scheduling problems, is the most frequently evaluated metric, being considered by 64% of single-objective and 73% of multi-objective papers (see Table 4). It is important to note that the work of (González-Neira et al., 2016) is the only one in the reviewed literature that addressed qualitative decision criteria. These authors included the importance of customers independently of the weight of jobs to represent the cost, in monetary terms, of tardy deliveries.

Table 4
Distribution of revised literature according objective function

Decision criteria	Single objective	With other objectives	Total
$Cmax$	64%	9%	73%
$Fmax$	0%	1%	1%
$Lmax$	1%	0%	1%
$Tmax$	1%	0%	1%
$\bar{C}$	5%	2%	7%
$\bar{C}^w$	0%	1%	1%
$\bar{F}$	1%	3%	4%
$\bar{F}^w$	1%	0%	1%
T	1%	5%	6%
T^w	1%	2%	3%
E	0%	2%	2%
E^w	0%	2%	2%
U	3%	1%	4%
WIP	1%	0%	1%
THR	1%	1%	2%
Cost of inventory	1%	0%	1%
Utilization of machines	0%	1%	1%
Cost of production system	0%	1%	1%
Total	81%		

4. Conclusions and research opportunities

We have surveyed 100 papers on FS and FFS scheduling under uncertainties published between 2001 and 2016. The amount of scientific work in this field has increased over the years. It is clear that with the growth of technology providing faster execution times, more complex problems can be solved. The vast majority of the reviewed works use probability distributions to model uncertainties, with the processing times followed by machine breakdowns being the most frequently analyzed uncertain parameters. This outcome of the current review represents an opportunity for researchers to deal with other parameters that in the real world are subject to uncertainties such as setup times, release dates, job weights, and so on. In fact, few studies take into account more than one uncertain parameter simultaneously, which is another opportunity for future work.

Regarding the objective function, most of the surveyed papers addressed the makespan as a single objective. Moreover, there is limited research in this field with multiple objectives. Therefore, future research might focus on other criteria such as flow time, lateness, completion time, tardiness, and their weighted counterparts, as well as the study of at least two objectives with different existing multi-objective methodologies. In addition, new research can be done to include qualitative decision criteria, since only one paper published during the period under study considered this type of objective.

With regard to the approaches to deal with uncertainties, stochastic methods, including simulation-optimization, have been employed most often. Robust methods have not been used as much as stochastic approaches and they present the problem that a possibility exists that an uncertainty with low probability may lead to elimination of good solutions. So, hybridization of stochastic approaches such as simulation-optimization with robust methods can overcome the conservativeness of robust approaches.

Finally, in reference to the optimization methods, metaheuristics present an increasing trend and cover more than 50% of reviewed research. Hybridization of metaheuristics combined with any of the four methods to deal with uncertainties and multi-criteria approaches is another line for future research.

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