Artificial Intelligence Review (2020) 53:501–593
https://doi.org/10.1007/s10462-018-9667-6

A state of the art review of intelligent scheduling

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Published online: 19 November 2018

Abstract
Intelligent scheduling covers various tools and techniques for successfully and efficiently solving the scheduling problems. In this paper, we provide a survey of intelligent scheduling systems by categorizing them into five major techniques containing fuzzy logic, expert systems, machine learning, stochastic local search optimization algorithms and constraint programming. We also review the application case studies of these techniques.

Keywords Intelligent scheduling · Fuzzy logic · Expert system · Machine learning · Stochastic local search optimization algorithms · Constraint programming

1 Introduction

With the rapidly developing global technology, today's different businesses face greater challenges for scheduling and sequencing. Because of the importance of scheduling problems, many researchers focused on this issue in the past decades. Scheduling involves the effective allocation of resources to activities over time so that satisfy all temporal and resource capacity constraints, optimize the different objective and generally is a process to satisfy the customers and manufacturers.

Due to the extent of scheduling problems, there are several classifications of scheduling problem in literature. Often, scheduling problems are distinguishable based on three factor involves: machine environment, job characteristics and objective function(s) to be minimized.

Machine environment covers single machine, multi-machine, parallel identical machines, uniform machines, unrelated machines, job shop, flow shop, open shop, flexible flow shop and flexible job shop problems.

Job characteristics contain: presence of preemption (resume or repeat), precedence constraints between jobs acyclic digraph, presence of release dates, preprocessing times are equal, presence of deadlines, batching problem, sequence dependent setup times, machine

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breakdowns, machine eligibility restrictions, permutation flow shop, presence of blocking in flow shop (limited buffer), no-wait in flow shop (limited buffer), recirculation in job shop (Graham et al. 1979). Two types of objective function are most common: bottleneck objective functions (like C_{max} and L_{max}) and sum objective functions (like $\sum Cj$ and $\sum wjTj$) (Bochtis 2010). Owing to the operational diversity and intrinsic difficulty of most scheduling problems, artificial intelligence techniques have a great place in the toolkit of the scheduling researchers. The field of artificial intelligence (AI) was introduced for the first time by McCarthy (1956) when organizing a conference at the Dartmouth College on intelligent machines. Schalkoff (1990) defines the field of artificial intelligence as follows (Schalkoff 1990):

> "Artificial intelligence includes problem-solving by methods modeled after natural activities and cognitive processes of humans using computer programs that simulate them".

About 40 years ago, scheduling was dominated by operation research but the advent of new methods such as artificial intelligence changed the situation. According to Brown et al. (1995a) and Ouelhadj and Petrovic (2009), these are four reasons for this change:

First, the solutions which obtain using intelligent approaches are more promising than traditional optimization approaches. Second, most scheduling problems belong to the class of NP-Hard problems and have high complexity. Third, intelligent approaches reduce the time needed to find the solutions compared to traditional optimization approaches. Fourth, the difficulty of traditional optimization approaches in capturing the problem formulation in a closed-form mathematical expression.

Because of these barriers, many researchers in scheduling have turned to artificial intelligence approaches. There are several studies in the literature which look at the problems of scheduling using artificial intelligence approaches. In 2001, Rajpathak categorized the various techniques developed for the intelligent scheduling into seven categories which are heuristic scheduling approach, constraint-based scheduling, fuzzy approaches, neural network approach, iterative improvement techniques, distributed scheduling, and meta-scheduling (Rajpathak 2001). Moreover, Abd classified the artificial intelligence approaches under five main categories, i.e. fuzzy logic, neural networks, genetic algorithm, ant colony, and expert systems (Abd 2015). In addition, Brown et al. provided a survey of intelligent scheduling systems based on artificial and computational intelligence techniques. They believed that these techniques could be grouped into six main categories, i.e. expert systems, machine learning methods, genetic algorithms, simulated annealing, neural networks, and hybrid systems (Abd 1995).

Considering all these categories, in the current study, we investigate five major artificial intelligence techniques for scheduling problems. These techniques are:

1. Fuzzy logic.
2. Expert systems.
3. Machine learning (case based reasoning, inductive learning, and neural networks).
4. Stochastic local search optimization algorithms (simulated annealing, tabu search, particle swarm optimization, ant colony optimization, and evolutionary approaches).
5. Constraint programming.

The paper has the following structure: In Sects. 2–6, brief definitions and concept of these five major techniques of intelligent scheduling are presented and then an extensive review of the scheduling literature under these intelligent techniques in each section is provided. The literature in scheduling is immense and we make no claims of completeness in this survey.

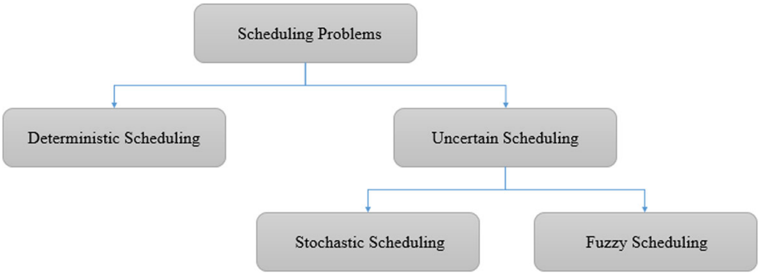

Fig. 1 Classification of the scheduling problems (Nagar et al. 1995)

Instead, we attempted to cover the most important and practical techniques from intelligent scheduling systems. Finally, concluding remarks are presented in Sect. 7.

2 Fuzzy scheduling

Fuzzy logic is one of the widespread techniques in computational intelligence. From the beginning of fuzzy concept appearance, fuzzy logic applications on the scheduling problems have increased. The real-life scheduling problems often have several uncertainties. The solutions of these problems can provide deeper insights to the decision makers than those of deterministic problems. Fuzzy set theory, as the most important tool to model uncertainty, represents an attractive tool to aid research in production management.

The goal of this section is to provide an extensive review for the fuzzy machine scheduling. For this purpose, first, this section classifies and reviews the literature according to shop environments, including single machine, parallel machines, flow shop, job shop, and open shop problems. The principal advantage of fuzzy scheduling is the possibility of focusing on significant scheduling decisions.

Guiffrida and Nagi (1998) introduced four important motivations that fuzzy set theory is relevant to scheduling:

- Imprecision and vagueness are inherent in the decision maker's mental model. Thus, the decision maker's experience and judgment may be used to complement established theories to foster a better understanding of the problem.
- In the scheduling environment, the information required to formulate a model's objective, decision variables, constraints and parameters may be vague or not precisely measurable.
- Imprecision and vagueness as a result of personal bias and subjective opinion may further dampen the quality and quantity of available information.
- A fuzzy scheduling algorithm builds into the real system flexibility and adaptation to the uncertainty inherent in real environments.

2.1 Fuzzy machine scheduling (concepts and classification)

The earliest paper in the fuzzy scheduling appeared by Prade in 1979. One of the most popular classifications in scheduling problem is presented by Nagar et al. (Fig. 1).

As shown in Fig. 1, the scheduling process is divided into two classes of problems: deterministic scheduling and uncertain scheduling. Next, the uncertain scheduling problems are grouped into two types: fuzzy scheduling and stochastic scheduling in which stochastic

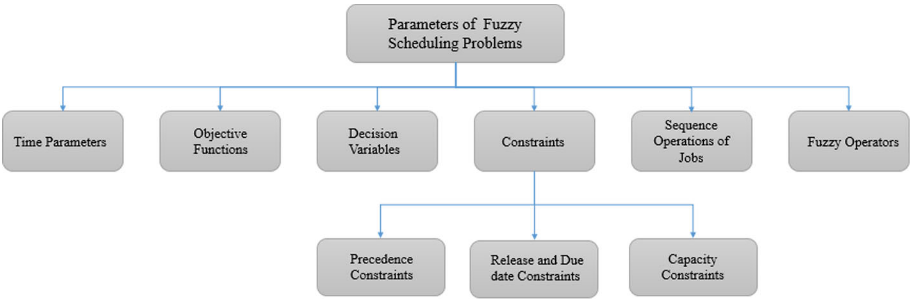

Fig. 2 Parameters of fuzzy scheduling problems (Abdullah and Abdolrazzagh-Nezhad 2014)

variable is used to indicate the processing constraints and parameters. On the other hand, fuzzy scheduling problems can be divided into type 1 and type 2 fuzzy. Given the nature of the problems, the scheduling process can classify into five classes of problems such as flow shop, job shop, open shop, single machine and parallel machines. The fuzzy set theory influences the scheduling problems through six parameters (Abdullah and Abdolrazzagh-Nezhad 2014). These parameters are illustrated in Fig. 2.

2.2 Fuzzy flow shop scheduling

In flow shop problems all jobs have the same processing order through the machines. The order of the jobs on each machine can be different. Several fuzzy flow shop models have been proposed in the literature over the past few years.

McCahon and Lee (1992) modified the Campbell, Dudek and Smith (CDS) job sequencing algorithm to accept trapezoidal fuzzy processing times. In their work, deterministic sequences were developed, and then fuzzy makespans and fuzzy job mean flow times were calculated using fuzzy arithmetic (McCahon and Lee 1992).

Ishibuchi et al. (1994) formulated a fuzzy flow shop scheduling problem where the due date of each job is given as a fuzzy set. The objective function of the formulated problem was to maximize the minimum grade of satisfaction over given jobs. Several local search algorithms including multi-start descent, simulated annealing and tabu search algorithms were applied to solve the problem (Ishibuchi et al. 1994).

Murata et al. (1996) examined the performance of genetic algorithms in order to specify some genetic operators and parameters for the flow shop scheduling problem. They showed that the genetic algorithm was much superior to a random sampling technique but it was a bit inferior to other search algorithms such as local search, tabu search and simulated annealing. They examined two hybrid algorithms: genetic local search and genetic simulated annealing in order to improve the performance of the genetic algorithm (Murata et al. 1996).

Hong and Wang (2000) proposed a fuzzy scheduling algorithm for scheduling jobs in flexible flow shops with two machine centers. They used triangular fuzzy longest processing time (LPT) algorithm to allocate jobs and then used a triangular fuzzy Johnson algorithm to deal with sequencing the tasks. The scheduling results were a fuzzy set and could help system managers have broader views of scheduling and made good analysis (Hong and Wang 2000).

Peng and Song (2003) investigated the flow shop scheduling problem in a fuzzy environment by means of credibility measure. The authors also presented a hybrid intelligent algorithm to solve the proposed models and provide efficient computational studies (Peng and Song 2003).

Wu and Xingsheng (2004) used the fuzzy numbers to denote the uncertainty of processing time in flow shop scheduling and developed the multiple objective scheduling models for flow shop scheduling problems with fuzzy processing time. The multiple objectives is converted into single one by a weighted method, and the fuzzy optimal problem then transformed to a deterministic problem by Zimmermann algorithm (Wu and Xingsheng 2004).

Petrovic and Xueyan (2006) presented a new approach to two-machine flow shop problem with uncertain processing times. Their paper deals with the problem of optimization of job sequence in a two-machine flow shop problem in the presence of uncertainty. It is assumed that the processing times of jobs on the machines are described by triangular fuzzy sets. A new optimization algorithm based on Johnson's algorithm for deterministic processing times and on an improvement of McCahon and Lee's algorithm is developed and presented (Petrovic and Xueyan 2006).

Kumar et al. (2007) investigated the performance of the two algorithms (Genetic Algorithm and Particle Swarm Optimization) when applied to flow shop scheduling with fuzzy due dates. An attempt has been made to hybridize the two algorithms. It is established that the hybrid algorithm (PSOGA) produces better results on problems of larger size when compared to the individual performance of the algorithms (Kumar et al. 2007).

Lai and Wu (2008) investigated the scheduling problems with fuzzy processing times and fuzzy due dates. The concepts of earliness and tardiness are interpreted by using the concepts of possibility and necessity measures that were developed in fuzzy sets theory. Many types of objective function will be taken into account through the different combinations of possibility and necessity measures. The purpose of their paper is to obtain the optimal schedules based on these objective functions (Lai and Wu 2008).

Rezaie et al. (2009) presented a novel, mixed-integer programming model for scheduling of n independent jobs in a flexible flow shop (FFS) system with blocking processor, sequence-dependent setup times, and unrelated parallel machines. Due dates are uncertain in nature and assumed to be fuzziness. Here, the main objective is to maximize the weighted additive of the satisfaction level of meeting due dates. Since the problem is known to be NP-hard in the strong sense, only a few test problems in small sizes is solved by the Lingo software package in order to show the validity of the proposed model (Rezaie et al. 2009).

Sheibani (2010) described a polynomial-time heuristic for the permutation flow shop scheduling problem with the makespan criterion. The proposed method consists of two phases: arranging the jobs in priority order and then constructing a sequence. A fuzzy greedy evaluation function is employed to prioritize the jobs for incorporating into the construction phase of the heuristic (Sheibani 2010). Azadeh et al. (2010) presented a flexible artificial neural network–fuzzy simulation (FANN–FS) algorithm for solving the multi-attribute combinatorial dispatching (MACD) decision problem. Xu et al. (2010a) presented a new shuffled frog leap algorithm (NSFLA) for the flow shop scheduling problem (FSSP) with uncertain processing time.

Dugardin et al. (2011) solved a multi-objective scheduling of a reentrant hybrid flow shop. The objectives were considered makespan and total tardiness minimization. This problem is solved using L-Ant (a Lorenz multi-objective ant colony system algorithm) and an improved version of this algorithm called fuzzy Lorenz ant colony system (Dugardin et al. 2011). Ling et al. (2011) proposed a hybrid fuzzy logic-based particle swarm optimization (PSO) with cross-mutated operation method for the minimization of makespan in permutation flow shop scheduling problem. In the proposed hybrid PSO, the fuzzy inference system is applied to determine the inertia weight of PSO and the control parameter of the proposed cross-mutated operation by using human knowledge (Ling et al. 2011).

Gupta et al. (2012) introduced the concept of fuzziness in specially structured n jobs, 2 machines flow shop scheduling problem in which the processing time of jobs are uncertain and are represented by a trapezoidal fuzzy membership function. The objective of the paper is to develop a heuristic algorithm to minimize the rental cost of the machines taken on rent under a specified rental policy without violating the value of the maximum makespan as proposed by Johnson's for a two-stage specially structured flow shop scheduling (Gupta et al. 2012). Huang et al. (2012) proposed an improved algorithm to search optimal solutions to the flow shop scheduling problems with fuzzy processing times and fuzzy due dates. A longest common substring method is proposed to combine with the random key method (Huang et al. 2012).

Behnamian and Ghomi (2014) considered a bi-objective hybrid flowshop scheduling problems with fuzzy tasks' operation times, due dates and sequence-dependent setup times. To solve this problem, they proposed a bi-level algorithm to minimize two criteria, namely makespan, and the sum of the earliness and tardiness, simultaneously. In the first level, the population will be decomposed into several subpopulations in parallel and each subpopulation is designed for a scalar bi-objective. In the second level, non-dominant solutions obtained from sub-population bi-objective random key genetic algorithm (SBG) in the first level will be unified as one big population. In the second level, for improving the Pareto-front obtained by SBG, based on the search in Pareto space concept, a particle swarm optimization (PSO) is proposed (Behnamian and Ghomi 2014). Ambika and Uthra (2014) presented a branch and bound technique in flow shop scheduling problem with imprecise processing times, being the objective to minimize the total elapsed time. The processing times are described by triangular membership functions. Job sequences are constructed with respect to branch and bound technique by fuzzy processing time (Ambika and Uthra 2014).

Nailwal et al. (2015) described an algorithm incorporating the uncertain processing time and setup time of n-jobs on two machines to minimize the rental cost of machines.

Wang et al. (2016a) presented a fuzzy logic-based hybrid estimation of distribution algorithm (FL-HEDA) to address distributed permutation flow shop scheduling problems (DPFSPs) under machine breakdown with makespan criterion. In order to explore more promising search space, FL-HEDA hybridizes the probabilistic model of estimation of distribution algorithm with crossover and mutation operators of a genetic algorithm to produce new offspring. In the FL-HEDA, a novel fuzzy logic-based adaptive evolution strategy (FL-AES) is adapted to preserve the population diversity by dynamically adjusting the ratio of offspring generated by the probabilistic model. Moreover, a discrete-event simulator that models the production process under machine breakdown is applied to evaluate expected makespan of offspring individuals (2016b). Sathish and Ganesan (2016) proposed a method to minimize the total makespan; without converting the fuzzy processing time to classical numbers by using a new type of fuzzy arithmetic and a fuzzy ranking method. Mittal et al. (2016) established a linkage between a priority queue networks having an intermediate queue with a flow shop scheduling under fuzzy environment. The queue discipline before the servers is considered on the basis of high priority while intermediate queue service is taken to be the low priority. It is usually assumed that the various arrival rates, service rates and the processing time of the task (jobs) are either exact or probabilistic (Mittal et al. 2016). The most important studies in the field of fuzzy flow shop scheduling are summarized in Table 1.

Table 1 The most important studies in the field of fuzzy flow shop scheduling

Nos.	Authors	Years	Application or method	References
1	McCahon and Lee	1992	Fuzzy job sequencing	McCahon and Lee (1992)
2	Ishibuchi et al.	1994	Flow shop scheduling with fuzzy due date	Ishibuchi et al. (1994)
3	Hong and Wang	2000	Fuzzy LTP algorithm	Hong and Wang (2000)
4	Peng and Song	2003	Fuzzy flow shop scheduling models based on credibility measure	Peng and Song (2003)
5	Wu and Gu	2004	Multiple objective scheduling model with fuzzy processing time	Wu and Gu (2004)
6	Kumar et al.	2007	Hybrid algorithm based on genetic and PSO algorithms for a flow shop problem with fuzzy due date	Kumar et al. (2007)
7	Lai and Wu	2008	Fuzzy due dates based on the concepts of possibility and necessity measure	Lai and Wu (2008)
8	Sheibani	2010	Fuzzy greedy polynomial-time heuristic	Sheibani (2010)
9	Azadeh et al.	2010	Flexible artificial neural network–fuzzy simulation algorithm for solving the MACD decision problem	Azadeh et al. (2010)
10	Xu et al.	2010	Shuffled frog leap algorithm for flow shop scheduling problem with fuzzy processing time	Xu et al. (2010)
11	Dugardin et al.	2011	Fuzzy Lorenz ant colony algorithm	Dugardin et al. (2011)
12	Ling et al.	2011	Hybrid fuzzy logic-based PSO algorithm	Ling et al. (2011)
13	Ambika and Uthra	2014	Branch and bound technique for a flow shop problem with fuzzy processing times	Ambika and Uthra (2014)
14	Nailwal et al.	2015	Rental cost minimization for two-stage flow shop scheduling with fuzzy processing and setup times	Nailwal et al. (2015)
15	Wang et al.	2016	Fuzzy hybrid estimation of distribution algorithm for DPFS problems under machine breakdown	Wang et al. (2016)
16	Sathish and Ganesan	2016	Three machines flow shop fuzzy scheduling with double transport facility	Sathish and Ganesan (2016)
17	Mittal et al.	2016	Fuzzy priority queue system	Mittal et al. (2016)

2.3 Fuzzy job shop scheduling

In job shop scheduling problems, operations of a job totally ordered and each job follows a predetermined route and a machine may be visited more than once by a job.

Turksen et al. (1993) constructed a subjective fuzzy model to solve a job releasing and dispatching decision problem in a job shop environment. The selected input variables were "priority", "slack time" and "requested start time" for job release decisions; "priority", "slack time" and "remaining processing time" for job dispatching decisions. The output variable was the "selectability" (Turksen et al. 1993).

Dubois et al. (1995) proposed an extension of the constraint-based approach to job shop scheduling that accounts for the flexibility of temporal constraints and the uncertainty of operation durations. They formulated a simple mathematical model of job shop scheduling under preference and uncertainty, relating it to the formal framework of constraint-satisfaction problems in artificial intelligence (Dubois et al. 1995). Fortemps (1995) investigated job shop scheduling problems with fuzzy or flexible durations.

Fortemps (1997) published a paper entitled "Job shop scheduling with imprecise durations: a fuzzy approach". In this paper, the fuzzy numbers are considered as the sets of possible probabilistic distributions and after a review of some issues concerning fuzzy numbers, discusses the determination of a unique optimal solution of the problem. Then, he cast a metaheuristic (simulated annealing-SA) to this particular framework for optimization (Fortemps 1997).

Sakawa and Mori (1999) by considering the imprecise or fuzzy nature of the data in real-world problems, formulated job shop scheduling problems with fuzzy processing time and fuzzy due date and proposed a genetic algorithm which is suitable for solving the formulated problems.

Subramaniam et al. (2000) proposed a fuzzy scheduler that uses the prevailing conditions in the job shop to select dynamically the most appropriate dispatching rule from several candidate rules.

Sakawa and Kubota (2001) discussed fuzzy job shop scheduling considering the fuzzy processing time and the fuzzy due time, and formulated the fuzzy job shop scheduling problem considering two objects, namely, minimization of the maximum fuzzy completion time and maximization of the average agreement index. In this paper, for each of the functions in the formulated two-objective fuzzy job shop scheduling problem, the fuzzy goal of the decision-maker is specified by a linear membership function, and then an approximate solution method is proposed, where the genetic algorithm is used to solve the problem, which integrates the membership functions by the fuzzy decision formulated by Bellman and Zadeh (Sakawa and Kubota 2001).

Yun (2002) proposed a new genetic algorithm (GA) with the fuzzy logic controller (FLC) for dealing with preemptive job shop scheduling problems (p-JSP) and non-preemptive job shop scheduling problems (np-JSP). The proposed algorithm considers the preemptive cases of activities among jobs under single machine scheduling problems (Yun 2002). In another paper, Lin (2002) considered a fuzzy job shop scheduling problem with imprecise processing times. He used interval-valued fuzzy numbers for the representation of vague processing times (Lin 2002).

Wan and Wan (2003) proposed an approach for the job shop scheduling problem by using tabu search with fuzzy reasoning. There are two parts in this approach: tabu search module and fuzzy reasoning module that performs the function of adaptive parameter adjustment in tabu search (Wan and Wan 2003). Lin (2003) investigated a fuzzy approach to the job shop scheduling problem based on imprecise processing times. Lin first used triangular fuzzy numbers to represent imprecise processing times, and then constructed a fuzzy job shop scheduling model to solve the problem (Lin 2003).

Bilkay et al. (2004) presented a two-stage approach for fuzzy job shop problem: in the first stage, they proposed a fuzzy logic-based algorithm for assigning priorities to part types that are to be machined and in the second stage, they presented an operation-machine allocation and scheduling algorithm. Luh et al. (1999) described the corresponding conceptions of Partial Flexible Job shop Scheduling problems then an improved scheduling model based on fuzzy logic is given to deal with the partial flexible job shop scheduling problems in the fuzzy environment.

Fayad and Petrovic (2005) proposed a multi-objective genetic algorithm to deal with a real-world fuzzy job shop scheduling problem. In this paper, fuzzy sets are used to model uncertain due dates and processing times of jobs. The objectives considered are average tardiness and the number of tardy jobs. Fuzzy sets are used to represent satisfaction grades for the objectives taking into consideration the preferences of the decision maker. A genetic algorithm is developed to search for the solution with maximum satisfaction grades for the objectives (Fayad and Petrovic 2005).

Gu et al. (2006) presented a paper entitled "Optimization for fuzzy flexible job shop scheduling based on genetic algorithm". In this paper, a flexible job shop scheduling model in a fuzzy production environment is given at first. Secondly, the best solution based on genetic algorithm according to the objective function of the minimum makespan is presented (Gu et al. 2006). Feng et al. (2006) introduced the flexible job shop scheduling problem with uncertain temporal information, then they described α cut, the interval-valued fuzzy set and corresponding concepts. Next, an improved flexible job shop scheduling model based on interval-valued trapezoidal fuzzy number is given to deal with fuzzy scheduling problems (Feng et al. 2006). Kılıç and Kahraman (2006) stated ant algorithm can solve job shop scheduling (JSS) problems in a reasonable time. Lu et al. (2006) introduced the fuzzy operational duration and fuzzy due date problems in the practical job shop scheduling environment then described the signed distance, the interval numbers distance, and corresponding concepts. Then, to deal with the earliness/tardiness penalty problems, an improved genetic optimization approach is used to frame the job shop scheduling model which is based on fuzzy numbers signed distance and interval numbers distance (Lu et al. 2006). Song (2006) proposed a combined strategy of algorithms to solve fuzzy job shop scheduling problems. This strategy adopts genetic algorithms and ant colony algorithms as a parallel asynchronous search algorithm. In addition, according to the characteristics of fuzzy job shop scheduling, they proposed a concept of the critical operation and designed a new neighborhood search method based on the concept. Furthermore, an improved TS algorithm is designed, which can improve the local search ability of genetic algorithms and ant colony algorithms (Song 2006).

Xing et al. (2007) proposed an ant colony optimization with linguistically quantified decision functions (ACO-LQDF) for the flexible job shop scheduling problems (FJSSP). The novelty of the proposed approach is the interactive and fuzzy multi-objective nature of the Ant Colony Optimization (ACO) that considers the aspiration levels set by the decision maker (DM) for the objectives (Xing et al. 2007). Zarandi et al. (2007a) presented a fuzzy expert system for textile manufacturing system using fuzzy cluster analysis. The proposed approach consists of two phases. The first phase was developed with an unsupervised learning and involved a baseline design to effectively identify a prototype fuzzy system. At the second phase, a fine-tuning process was done to adjust the parameters identified in the baseline design, subject to supervised learning. Finally, the proposed approach was tested and validated by applying it to scheduling system of a textile industry and comparing the results with a Sugeno-type fuzzy system modeling that used subtractive clustering in its structure identification stage (Zarandi et al. 2007b). Zarandi et al. (2007a) introduced the scheduling of robotic cells with two and three machines with fuzzy methodology. For generating the optimal part sequencing in the cells, the Gilmore and Gomory algorithm was modified and instead, a fuzzy Gilmore and Gomory algorithm was developed (Zarandi et al. 2007b).

Lei (2008) addressed multi-objective job shop scheduling problems with fuzzy processing time and due date in such a way to provide the decision-maker with a group of Pareto optimal solutions. Lei presented a new priority rule-based representation method. In this paper, the problems are converted into continuous optimization ones to handle the problems by using particle swarm optimization (Lei 2008). Niu et al. (2008) presented a paper entitled “Particle swarm optimization combined with genetic operators for job shop scheduling problem with fuzzy processing time”. In this paper, job shop scheduling problem with fuzzy processing time is addressed. The processing time is described by triangular fuzzy numbers. The objective is to find a job sequence that minimizes the makespan and the uncertainty of the makespan by using an approach for ranking fuzzy numbers (Niu et al. 2008).

Fangming and Qiong (2009) presented a hybrid PSO (HPSO) algorithm for fuzzy job shop scheduling problem. This algorithm uses the processing encoding random key to generate the initial population and takes parameter uniformity crossover operator as particle swarm’s update operator (Fangming and Qiong 2009).

Lei (2010a) presented the fuzzy job shop scheduling problem with availability constraints. The objective is to find a schedule that maximizes the minimum agreement index subject to periodic maintenance, non-resumable jobs and fuzzy due date. A random key genetic algorithm (RKGA) is proposed for the problem, in which a novel random key representation, a new decoding strategy incorporating maintenance operation and discrete crossover (DX) are used (Lei 2010a). In another paper, Lei (2010b) presented a flexible job shop scheduling problem with fuzzy processing time. In this paper, an efficient decomposition-integration genetic algorithm (DIGA) is developed for the problem to minimize the maximum fuzzy completion time. DIGA uses a two-string representation, an effective decoding method and the main population (Lei 2010b). Also, Lei (2010a) published a paper entitled “Solving fuzzy job shop scheduling problems using random key genetic algorithm”. This paper addresses job shop scheduling problems with fuzzy processing time and fuzzy trapezoid or doublet due date. In this paper, an efficient random key genetic algorithm (RKGA) is suggested to maximize the minimum agreement index and to minimize the maximum fuzzy completion time. In RKGA, a random key representation and a new decoding strategy are proposed and two-point crossover (TPX) and discrete crossover (DX) are considered (Lei 2010b).

Hu et al. (2011) investigated the job shop scheduling problems with fuzzy processing time and fuzzy due date. They introduced the ranking concept among fuzzy numbers based on possibility and necessity measures which are developed in fuzzy sets theory and proposed several novel objective functions. Their purpose is to obtain the optimal schedules based on these objective functions (Hu et al. 2011).

Lei and Guo (2012) proposed an efficient swarm-based neighborhood search algorithm (SNSA) for the fuzzy flexible job shop scheduling problem. In SNSA, ordered operation-based representation is used to indicate the solution of operation sequence sub-problem and machine assignment sub-problem is converted into a cell formation one, in which machines are regarded as cells and operations are allocated into cells (Lei and Guo 2012). Zhang et al. (2012b) considered fuzzy flexible job scheduling problems with makespan and maximum machine workload and proposed a multi-objective swarm-based neighborhood search (MOSNS). Li et al. (2012) proposed a hybrid particle swarm optimization (PSO) algorithm for solving the job shop scheduling problem with fuzzy processing times. The objective is to minimize the maximum fuzzy completion time, i.e., the fuzzy makespan. This algorithm performs global explorative search, while the tabu search (TS) conducts the local exploitative search (Li et al. 2012).

Wang et al. (2013) proposed an effective estimation of distribution algorithm (EDA) to solve the flexible job shop scheduling problem with fuzzy processing time. They presented a probability model to describe the probability distribution of the solution space. In this paper, a mechanism is provided to update the probability model with the elite individuals (Wang et al. 2013). Li and Pan (2013) proposed a hybrid algorithm combining particle swarm optimization (PSO) and tabu search (TS) to solve the job shop scheduling problem with fuzzy processing time. The object is to minimize the maximum fuzzy completion time. In the proposed algorithm, PSO performs the global search, i.e., the exploration phase, while TS conducts the local search, i.e., the exploitation process (Li and Pan 2013). Zarandi and Azad (2013) proposed an interval type 2 fuzzy (IT2F) multi-agent based expert system for scheduling of steel production. They proposed an IT2F based hybrid strategy that combined IT2F programming and IT2F contract net protocol (CNP), where the variables (e.g. due date, completion time and processing time) that gained from manufacturing experts, were presented by IT2F membership functions (Zarandi and Azad 2013).

Tran et al. (2014) investigated the use of a multi-objective genetic algorithm to address job shop scheduling problems (JSPs) with uncertain durations. Uncertain durations in a JSP are expressed by means of triangular fuzzy numbers (TFNs). Instead of using expected values as in other work, they considered all vertices of the TFN representing the overall completion time. As a consequence, the proposed approach tries to obtain a schedule that optimizes the three component scheduling problems (corresponding to the lowest, most probable, and largest durations) all at the same time (Tran et al. 2014). Chen et al. (2014) proposed a novel adaptive immune-genetic algorithm (CAGA) to solve fuzzy job shop scheduling problems (FJSSP). CAGA manipulates a number of individuals to involve the progress of clonal proliferation, adaptive genetic mutations, and clone selection. The main characteristic of CAGA is the usage of clone proliferation to generate more clones for fitter individuals which undergo the adaptive genetic mutations, thus leading a fast convergence (Chen et al. 2014).

Xu et al. (2015) proposed an effective teaching–learning-based optimization algorithm (TLBO) to solve the flexible job shop problem with fuzzy processing time (FJSPF). First, they used a special encoding scheme to represent solutions, and a decoding method is employed to transfer a solution to a feasible schedule in the fuzzy sense. Second, a bi-phase crossover scheme based on the teaching–learning mechanism and special local search operators are incorporated into the search framework of the TLBO to balance the exploration and exploitation capabilities (Xu et al. 2015). Lin (2015) combined the biogeography-based optimization with some heuristics to construct an effective hybrid algorithm for solving the fuzzy flexible job shop scheduling problem. Huang and Süer (2015) proposed a dispatching rule-based genetic algorithm with fuzzy satisfaction levels (FRGA) to solve the multi-objective manufacturing scheduling problem. The objective is to develop a decision-making platform which appropriately handles conflicts among different performance measures in a manufacturing system. The proposed method focuses on a job shop scheduling problem with the objective of minimizing makespan, average flow time, maximal tardiness and total tardiness. Chromosome embeds the dispatching rules over the time period to help machine pick up the job from its queue (Huang and Süer 2015). Thammano and Teekeng (2015) proposed a novel metaheuristic algorithm, which is a modification of the genetic algorithm. This proposed algorithm introduces two new concepts to the standard genetic algorithm: (1) fuzzy roulette wheel selection and (2) the mutation operation with the tabu list (Thammano and Teekeng

2015). Azadeh et al. (2015) proposed a novel hybrid algorithm based on computer simulation and adaptive neuro-fuzzy inference system (ANFIS) to select optimal dispatching rule for each machine in job shop scheduling problems (JSSPs) under uncertain conditions so that makespan is minimized.

Hsu et al. (2016) presented an agent-based fuzzy constraint-directed negotiation (AFCN) mechanism to solve distributed job shop scheduling problems (JSSPs). The scheduling problem is modeled as a set of fuzzy constraint satisfaction problems (FCSPs), interlinked by inter-agent constraints (Hsu et al. 2016). Gao et al. (2016) presented a paper entitled "Artificial bee colony algorithm for scheduling and rescheduling fuzzy flexible job shop problem with new job insertion". In this paper, a two-stage artificial bee colony (TABC) algorithm with several improvements is proposed to solve the flexible job shop scheduling problem (FJSP) with fuzzy processing time and new job insertion constraints. Also, several new solution generation methods and improvement strategies are proposed and compared with each other. The objective is to minimize the maximum fuzzy completion time (Gao et al. 2016). The most important studies in the field of fuzzy job shop scheduling are summarized in Table 2.

2.4 Fuzzy open shop scheduling

In these problems, each job must be processed on each machine and there are no ordering constraints on operations. Ishii et al. (1992) investigated scheduling problems with fuzzy due dates, that is, a generalized two machine open shop scheduling problem with fuzzy due dates and an identical machine scheduling problem with fuzzy due dates.

Konno and Ishii (2000) presented a model for a preemptive open shop scheduling problem and introduced constraints due to fuzzy resource and allowable time.

Seraj et al. (2009) proposed a bi-objective mixed-integer mathematical programming for an open shop scheduling problem (OSSP) that minimizes the mean tardiness and the mean completion time. To obtain the efficient (Pareto-optimal) solutions, a fuzzy multi-objective decision making (MODM) approach is applied (Seraj et al. 2009).

González-Rodríguez et al. (2010) considered the fuzzy open shop scheduling problem, where task durations are assumed to be ill-known and modeled as triangular fuzzy numbers. They proposed a neighborhood structure for local search procedures, based on reversing critical arcs in the associated disjunctive graph. They provided a thorough theoretical study of the structure and, in particular, prove that feasibility and asymptotic convergence hold (González-Rodríguez et al. 2010).

Noori-Darvish and Tavakkoli-Moghaddam (2011) presented a new bi-objective possibilistic mixed-integer linear programming model for an open shop scheduling problem. Machine-dependent setup times, fuzzy processing times and fuzzy due dates with triangular possibility distributions are the main constrain of this model. The objectives are to minimize the total weighted tardiness and total weighted completion times. In their work, an interactive fuzzy programming solution approach proposed by Torabi and Hassini (TH) is applied to convert the original model into an auxiliary single-objective crisp model (Noori-Darvish and Tavakkoli-Moghaddam 2011).

Jafari et al. (2012) considered the fuzzy open shop scheduling problem with parallel machines in each working stage, where processing times are vague and are represented by fuzzy numbers. In their work, an open shop scheduling problem with parallel machines in each working stage under this condition is close to the real production scheduling conditions. A mixed-integer fuzzy programming (MIFP) model is presented to formulate the problem

Table 2 The most important studies in the field of fuzzy job shop scheduling

Nos.	Authors	Years	Application or method	References
1	Turksen et al.	1993	Subjective fuzzy model to solve a job releasing and dispatching decision problem	Turksen et al. (1993)
2	Dubois et al.	1995	Constraint-based approach for job shop scheduling problem with fuzzy durations	Dubois et al. (1995)
3	Fortemps	1997	Metaheuristic approach for job shop scheduling problem with fuzzy durations	Fortemps (1997)
4	Subramaniam et al.	2000	Dynamic fuzzy selection of dispatching rules	Subramaniam et al. (2000)
5	Yun	2002	Genetic algorithm with fuzzy logic controller	Yun (2002)
6	Lin	2002	Fuzzy job shop scheduling based on ranking level	Lin (2002)
7	Wan and Wan	2003	Hybrid approach based on tabu search and fuzzy reasoning	Wan and Wan (2003)
8	Lu et al.	2004	Fuzzy partial flexible job shop scheduling problems	Lu et al. (2004)
9	Gu et al.	2006	Genetic algorithm for fuzzy flexible job shop scheduling problem	Gu et al. (2006)
10	Feng et al.	2006	Interval value fuzzy flexible job shop scheduling problem	Feng et al. (2006)
11	Kılıç and Kahraman	2006	Fuzzy ant colony optimization algorithm	Kılıç and Kahraman (2006)
12	Xing et al.	2007	Interactive fuzzy multi-objective ACO with linguistically quantified decision functions	Xing et al. (2007)
13	Zarandi et al.	2007	Fuzzy scheduling of textile manufacturing system	Zarandi et al. (2007a)
14	Zarandi et al.	2007	Two and three machine robotic cells fuzzy scheduling	Zarandi et al. (2007b)
15	Niu et al.	2008	Job shop scheduling problem with fuzzy processing time	Niu et al. (2008)
16	Lei	2010	Fuzzy job shop scheduling problem with availability constraints	Lei (2010a)
17	Lei	2010	Fuzzy job shop scheduling problems using random key genetic algorithm	Lei (2010c)
18	Hu et al.	2011	Ranking fuzzy number method based on possibility and necessity measures	Hu et al. (2011)
19	Zheng et al.	2012	Multi-objective swarm-based neighborhood search for fuzzy flexible job shop scheduling	Zheng et al. (2012)
20	Wang et al.	2013	ED algorithm for a job shop scheduling problem with fuzzy processing time	Wang et al. (2013)

Table 2 continued

Nos.	Authors	Years	Application or method	References
21	Zarandi and Azad	2013	Type 2 fuzzy multi agent based system for scheduling of steel production	Zarandi and Azad (2013)
22	Tran et al.	2014	Multi-objective genetic algorithm for job shop scheduling problem with fuzzy duration	Tran et al. (2014)
23	Xu et al.	2015	Teaching–learning-based optimization algorithm for the flexible job shop scheduling problem with fuzzy processing time	Xu et al. (2015)
24	Thammano and Teekeng	2015	Fuzzy roulette wheel selection	Thammano and Teekeng (2015)
25	Azadeh et al.	2015	Hybrid computer simulation-adaptive neuro-fuzzy inference system algorithm	Azadeh et al. (2015)
26	Hsu et al.	2016	Agent-based fuzzy constraint-directed negotiation mechanism	Hsu et al. (2016)
27	Gao et al.	2016	Artificial bee colony algorithm for scheduling and rescheduling fuzzy flexible job shop problem with new job insertion	Gao et al. (2016)

with the objective of minimizing makespan. To solve small-sized instances, an interactive fuzzy satisfying solution procedure is applied (Jafari et al. 2012).

Palacios et al. (2014b) considered a variant of the open shop problem where task durations are allowed to be uncertain and where uncertainty is modeled using fuzzy numbers. They proposed a particle swarm optimization (PSO) approach to minimize the schedule's expected makespan, using priorities to represent particle position, as well as a decoding algorithm to generate schedules in a subset of possibly active ones (Palacios et al. 2014b). In other work, they defined the concepts of necessary and possible β-robustness of schedules and set as their goal to maximize them. Additionally, they proposed to assess solution robustness by means of Monte Carlo simulations (Palacios et al. 2014a).

Palacios et al. (2015) considered a multi-objective open shop scheduling problem with uncertain processing times and flexible due dates, both modeled using fuzzy sets. They adopted a goal programming model based on lexicographic multi-objective optimization of both makespan and due date satisfaction and proposed a particle swarm algorithm to solve the resulting problem (Palacios et al. 2015). Ciro et al. (2015) presented a fuzzy ant colony optimization to solve an open shop scheduling problem with multi-skills resource constraints.

Gupta (2016) studied three-stage open shop scheduling problem in which job processing times on each machine are given in fuzzy environment and are presented by a triangular fuzzy membership function. The objective of the study is to obtain an optimal sequence through the branch and bound technique in order to minimize the total elapsed time (Gupta 2016). The most important studies in the field of fuzzy open shop scheduling are summarized in Table 3.

Table 3 The most important studies in the field of fuzzy open shop scheduling

Nos.	Authors	Years	Application or method	References
1	Ishii et al.	1992	Generalized two machine open shop scheduling problem with fuzzy due dates	Ishii et al. (1992)
2	Konno and Ishii	2000	Preemptive open shop scheduling problem with fuzzy constraints	Konno and Ishii (2000)
3	Seraj et al.	2009	Fuzzy multi-objective decision making approach for a open shop scheduling	Seraj et al. (2009)
4	González-Rodríguez et al.	2010	Open shop scheduling problem with fuzzy task duration	González-Rodríguez et al. (2010)
5	Noori-Darvish and Tavakkoli-Moghaddam	2011	Open shop scheduling problem with machine-dependent setup times, fuzzy processing and due date times	Noori-Darvish and Tavakkoli-Moghaddam (2011)
6	Jafari et al.	2012	Fuzzy open shop scheduling problem with parallel machines	Jafari et al. (2012)
7	Palacios et al.	2014	Robust swarm optimization for fuzzy open shop scheduling	Palacios et al. (2014b)
8	Palacios et al.	2014	β-robust solutions for the fuzzy open shop scheduling	Palacios et al. (2014a)
9	Palacios et al.	2015	Swarm lexicographic goal programming for fuzzy open shop scheduling	Palacios et al. (2015)
10	Ciro et al.	2015	Fuzzy open shop scheduling problem with multi-skills resource constraints	Ciro et al. (2015)
11	Gupta	2016	Three stage open shop scheduling by branch and bound technique under fuzziness	Gupta (2016)

2.5 Fuzzy single machine scheduling

In single machine problems, all the jobs must be processed on just one machine. Additionally, precedence constraints between the jobs may be given.

Custodio et al. (1994) addressed short-range planning and scheduling problems by using a non-classical approach supported by fuzzy theory. The proposed methodology uses a hierarchical structure, which includes three decision levels. The methodology approaches the tasks associated with each level using a heuristic formulation and solves the short-range planning and scheduling problems with a non-stationary policy. This method has the ability to use several criteria to generate a decision (Custodio et al. 1994). Han et al. (1994) proposed a generalized one machine maximum lateness problem with fuzzy due date and controllable machine speed. The objective of this method is to find an optimal schedule and optimal job wise machine speeds and to minimize the total sum of costs associated with job wise machine speeds and dissatisfaction with respect to completion times of jobs (Han et al. 1994).

Adamopoulos and Pappis (1996) proposed a fuzzy approach to the multiple criteria sequencing problem by using linguistic variables. The scheduling criteria are the common due date, the total earliness and tardiness and the controllable duration of the jobs' processing times. The aim is to determine the length of the processing times, to sequence the jobs in the machine and, finally, to determine the common due date in a near optimal way (Adamopoulos and Pappis 1996).

Liao and Liao (1998) considered a single machine scheduling problem with fuzzy due date and fuzzy processing time. This work formulated the objective of maximizing the minimum grade of satisfaction over given jobs. Two similar algorithms have been proposed to solve the problem with the polynomial time complexity (Liao and Liao 1998).

Chanas and Kasperski (2001) considered a single machine scheduling problem with fuzzy processing times and fuzzy due dates. In the first approach, it was assumed that for each job there is given a real-valued function f_i of its fuzzy completion time and its fuzzy due date. In the second one, each sequence of jobs was evaluated by a fuzzy maximum of weighted lateness and the objective is to maximize the degree of possibility that this value is not greater than a certain fuzzy number (fuzzy goal) that provided by a decision maker (Chanas and Kasperski 2001).

Wang et al. (2002) studied a ready time scheduling problem with fuzzy job processing times. In this work, the ready time scheduling model that maximizes the common ready time with crisp processing times is extended to one with fuzzy processing times. Optimal solutions for the scheduling model under several special conditions are developed, and a necessary condition that the optimal solution must satisfy when the jobs have different due dates and confidence levels is also established (Wang et al. 2002).

Muthusamy et al. (2003) considered a problem of scheduling jobs non-preemptively on a single machine subject to fuzzy time delay and precedence constraints. Schedules are evaluated not only by their makespan but also by degrees of satisfaction with time delays and precedence. This research illustrates that the problem of finding a set of non-dominated feasible schedules which contains exactly one schedule from each equivalence class of non-dominated feasible schedules can be solved in polynomial time (Muthusamy et al. 2003).

Chanas and Kasperski (2004) introduced the concepts of possible and necessary optimality of solutions in the single machine scheduling problem with fuzzy parameters. It is assumed that the optimal schedule in such a problem cannot be determined precisely. In the paper, the authors have shown how to calculate the degrees of possible and necessary optimality of a given schedule in one of the special cases of the single machine scheduling problems (Chanas and Kasperski 2004).

Itoh and Ishii (2005) proposed a single machine scheduling model where due dates for jobs were fuzzy random variables. In the model, jobs' processing times were crisp and the authors assigned satisfaction levels to jobs' completion times according to membership functions (Itoh and Ishii 2005).

Bagherpour et al. (2007) proposed a sequence-dependent single machine scheduling with earliness—tardiness penalty considerations using fuzzy setup time. It is assumed that setup times are dependent on both of, level of technology and the degree of operation's similarity (Bagherpour et al. 2007).

Duenas and Petrovic (2008) presented a multi-objective approach to a single machine scheduling problem in the presence of uncertainty. The two objectives defined are to minimize the maximum and the average tardiness of the jobs. A hybrid algorithm that combines a multi-objective genetic algorithm with local search is developed in order to find a job schedule that maximizes the aggregated satisfaction grade of the objectives (Duenas and Petrovic 2008).

Mehrabad and Pahlavani (2009) introduced a classic model of weighted single machine scheduling problem with the fuzzy processing times and fuzzy due dates. In the proposed model, two objectives are considered to be minimized: average tardiness and number of tardy jobs. They solved the model through three well-known metaheuristic algorithms namely simulated annealing, tabu search, and genetic algorithm albeit with some modifications (Mehrabad and Pahlavani 2009).

Tavakkoli-Moghaddam et al. (2010) presented a fuzzy multi-objective linear programming model to minimize the total weighted tardiness and makespan simultaneously in a single machine scheduling problem. In this work, a proposed method is applied with respect to the overall acceptable degree of the decision maker satisfaction (Tavakkoli-Moghaddam et al. 2010).

Ahmadizar and Hosseini (2011) considered a single-machine scheduling problem with a position-based learning effect and fuzzy processing times, simultaneously. The position-based learning effect of a job was assumed to be a function of its position and the processing times were triangular fuzzy numbers. A polynomial time algorithm was proposed for the problem where the objective was to minimize the total completion time (Ahmadizar and Hosseini 2011).

Li et al. (2012) considered a single machine batch scheduling problem with three objectives and proposed a solution procedure to find some non-dominated solutions. They defined non-dominated solutions consisting of batch size, batch number and allocation of jobs to batches. Based on a Lagrange relaxation procedure, they proposed an efficient algorithm for a sub-problem with a fixed upper limit of batch size and fixed batch number (Li et al. 2012).

In scheduling problems with learning effects, most research assumes that processing times are deterministic. Ahmadizar and Hosseini (2013) introduced a single-machine scheduling problem with a position-based learning effect and fuzzy processing times where the objective is to minimize the makespan. Two different polynomial-time algorithms were developed for the problem. The first solution methodology is based on the fuzzy chance-constrained programming, whereas the second is based on a method to rank fuzzy numbers (Ahmadizar and Hosseini 2013).

Li et al. (2005) investigated a problem of single machine parallel-batching problem with fuzzy due date and fuzzy precedence relation. Fuzzy due date denoted the degree of satisfaction with respect to completion times of jobs. Fuzzy precedence constraint expressed the satisfaction level about precedence between two jobs. In this paper, the objective was to minimize maximum completion time, maximize the minimum value of desirability of the fuzzy due date and the minimum value of desirability of the fuzzy precedence (Li et al. 2015).

Kır and Yazgan (2016) studied the scheduling problem for a fresh cheese production process on a single machine subject to varying due dates, penalty costs of earliness and tardiness and sequence-dependent setup times. In this study, the applicability of the schedules was appraised using fuzzy axiomatic design (FAD) to determine earliness and tardiness penalty costs. A hierarchical approach consisting of metaheuristic algorithms such as a tabu search and a genetic algorithm was proposed to generate proper schedules (Kır and Yazgan 2016). The most important studies in the field of fuzzy single machine scheduling are summarized in Table 4.

Table 4 The most important studies in the field of fuzzy single machine scheduling

Nos.	Authors	Years	Application or method	References
1	Han et al.	1994	Generalized one machine maximum lateness problem with fuzzy due date	Han et al. (1994)
2	Adamopoulos and Pappis	1996	Fuzzy-linguistic approach to a multi-criteria sequencing problem	Adamopoulos and Pappis (1996)
3	Chanas and Kasperski	2001	Single machine scheduling problem with fuzzy processing times and fuzzy due dates	Chanas and Kasperski (2001)
4	Wang et al.	2002	Ready time scheduling problem with fuzzy processing times	Wang et al. (2002)
5	Muthusamy et al.	2003	Fuzzy delays and fuzzy precedence constraints	Muthusamy et al. (2003)
6	Chanas and Kasperski	2004	Optimality of solutions in the single machine scheduling problem with fuzzy parameters	Chanas and Kasperski (2004)
7	Duenas and Petrovic	2008	Multi-objective genetic algorithm for fuzzy single machine problem	Duenas and Petrovic (2008)
8	Ahmadizar and Hosseini	2011	Position-based learning effect and fuzzy processing times	Ahmadizar and Hosseini (2011)
9	Li et al.	2012	Fuzzy batch size	Li et al. (2012)
10	Li et al.	2015	Single machine parallel-batching scheduling problem with fuzzy due date and fuzzy precedence relation	Li et al. (2015)
11	Kır and Yazgan	2016	Fuzzy axiomatic design for the penalty costs	Kır and Yazgan (2016)

2.6 Fuzzy parallel machines scheduling

The problems of parallel machine scheduling can be divided into three groups containing identical machines in parallel, machines in parallel with different speeds and unrelated machines in parallel that we survey these problems in this section.

Li et al. (1994) presented a fuzzy optimization methodology for scheduling single operation parts on identical machines with possible breakdowns. A fuzzy optimization formulation was first developed and Lagrangian relaxation technique was used to decompose the problem into part-level sub-problems and a fuzzy membership sub-problem. Fuzzy simulation developed to evaluate the performance of the resulting algorithm in a dynamic environment (Li et al. 1994).

Peng and Song (2001) presented a fuzzy programming expected value model for fuzzy parallel machine scheduling problem. Proposed model solved by a fuzzy simulation-based genetic algorithm.

Anglani et al. (2005) presented a robust approach for solving the scheduling problem of parallel machines with sequence dependent set-up costs. A fuzzy mathematical programming model was formulated by taking into account the uncertainty in processing times to provide the optimal solution as a trade-off between total set-up cost and robustness in demand satisfaction (Anglani et al. 2005).

Mok et al. (2007) proposed a fuzzification scheme to fuzzify the static standard time so as to incorporate some uncertainties, in terms of both job-specific and human-related factors, into the fabric cutting scheduling problem. A genetic optimization procedure was also proposed to search for fault-tolerant schedules using genetic algorithms, such that makespan and scheduling uncertainties were minimized (Mok et al. 2007).

Raja et al. (2008) studied the non-identical parallel-machine–earliness-tardiness non-common due date–sequence-dependent set-up time scheduling problem (NPETNDDSP) for jobs with varying processing times, where the objective was to minimize the sum of the absolute deviations of job completion times from their corresponding due dates for the different weighted earliness and tardiness combinations. A genetic algorithm-fuzzy logic approach (GA-Fuzzy) proposed to select the optimal weighted earliness-tardiness combinations in a non-identical parallel-machine environment (Raja et al. 2008).

Gharehgozli et al. (2009) introduced a mixed-integer goal programming model for a parallel-machine scheduling problem with sequence-dependent setup times, release dates, and two objectives. Two objectives are considered in the model to minimize the total weighted flow time and the total weighted tardiness simultaneously. An applicable methodology for solving the above fuzzy model was presented (Gharehgozli et al. 2009).

Balin (2011) considered the fuzzy parallel machine scheduling problem with fuzzy processing times (FPMSP) and a GA approach was proposed to minimize the maximum completion time. The GA was embedded in a simulation model for solving the problem. The use of simulation to implement the GA was preferred because of the evolutionary structure of the algorithm and the ability of the simulation to perform several tests using different random number sets (Balin 2011).

Alcan and BaşLıGil (2012) presented a kind of genetic algorithm based on machine code for minimizing the processing times in non-identical machine scheduling problem. Triangular fuzzy processing times were used in order to adapt the GA to non-identical parallel machine scheduling (Alcan and BaşLıGil 2012).

Torabi et al. (2013) proposed a multi-objective model for an unrelated parallel machine scheduling problem considering inherent uncertainty in processing times and due dates. The problem was characterized by non-zero ready times, sequence and machine-dependent setup times, and secondary resource constraints for jobs. This paper presented an effective multi-objective particle swarm optimization (MOPSO) algorithm to find a good approximation of Pareto frontier where total weighted flow time, total weighted tardiness, and total machine load variation were to be minimized simultaneously (Torabi et al. 2013).

Yeh et al. (2014) studied the parallel machine scheduling problem with fuzzy processing times and learning effects. The objective is to minimize the fuzzy makespan based on the possibility measure. Two heuristic algorithms, the simulated annealing algorithm, and the genetic algorithm, were proposed to solve the scheduling problem (Yeh et al. 2014).

Rostami et al. (2015) proposed a non-identical parallel machine multi-objective scheduling problem in which both the deterioration and learning effects had been considered. Due to the uncertainty of the parameters in real-world systems, processing times and due dates of jobs were represented here with triangular fuzzy numbers. A nonlinear mathematical model was provided based on fuzzy chance-constrained programming (FCCP) with the aim to minimize two objective functions, namely total earliness/tardiness (ET) and maximum completion time

Table 5 The most important studies in the field of fuzzy parallel machine scheduling

Nos.	Authors	Years	Application or method	References
1	Peng and Song	2001	Fuzzy simulation-based genetic algorithm	Peng and Song (2001)
2	Anglani et al.	2005	Fuzzy scheduling of parallel machines with sequence-dependent set-up costs	Anglani et al. (2005)
3	Mok et al.	2007	Fuzzification scheme for the static standard time	Mok et al. (2007)
4	Raja et al.	2008	Genetic algorithm-fuzzy logic to select the optimal weighted earliness-tardiness combinations	Raja et al. (2008)
5	Gharehgozli et al.	2009	Fuzzy-mixed-integer goal programming model	Gharehgozli et al. (2009)
6	Torabi et al.	2013	Fuzzy multi-objective unrelated parallel machines scheduling problem	Torabi et al. (2013)
7	Yeh et al.	2014	Fuzzy processing times and learning effects	Yeh et al. (2014)
8	Rostami et al.	2015	Multi-objective fuzzy parallel machine scheduling with job deterioration and learning effects	Rostami et al. (2015)

of jobs. Then, a multi-objective branch and bound algorithm was provided by introducing an effective lower bound in order to obtain a Pareto optimal front (Rostami et al. 2015). The most important studies in the field of fuzzy parallel machine scheduling are summarized in Table 5.

2.7 Strengths and weaknesses of fuzzy logic

In this subsection, a summary of the strengths and weaknesses of fuzzy logic is presented (Jain and Martin 1999; Davidrajuh 2001).

2.7.1 Strengths of fuzzy logic

- Fuzzy logic offers fast inference.
- Fuzzy logic converts complicated problems into simpler problems using approximate reasoning.
- Fuzzy logic can effectively model the uncertainty of a system.
- Fuzzy logic avoids the complex mathematical modeling. Thus, it is able to reflect nonlinearity and variation over time for complex systems.
- Fuzzy logic can handle problems with imprecise and incomplete data.
- Fuzzy logic is easy to implement using both software on existing microprocessors or dedicated hardware.

- Fuzzy logic-based solutions are cost effective for a wide range of applications when compared to traditional methods.

2.7.2 Weaknesses of fuzzy logic

- Tuning: A significant time investment is needed to correctly tune membership functions and adjust rules to obtain a good solution.
- Fuzzy logic does not guarantee completeness: it is up to the designer to include all the fuzzy rules connecting all possible combinations between the input and output parameters.
- Generating fuzzy rule base is difficult: Generating the antecedent of a fuzzy rule is easy, but generating the consequent of a fuzzy rule is not easy due to the fact that it demands a deep understanding of the process dynamics.
- As the system complexity increases, it becomes more challenging to determine the accurate set of rules and membership functions to describe system behavior. Moreover, more rules are needed, and it becomes increasingly difficult to relate these rules.
- Using fixed geometric-shaped membership functions limits system knowledge more in the rule base than in the membership function base. This results in requiring more system memory and processing time.
- Fuzzy logic uses heuristic algorithms for defuzzification, rule evaluation, and antecedent processing. Heuristic algorithms can cause problems mainly because heuristics do not guarantee satisfactory solutions that operate under all possible conditions.
- The generalization capability of fuzzy logic is poor compared to other methods such as neural nets. The generalization capability is important in order to handle unforeseen circumstances.
- Conventional fuzzy logic cannot generate rules that will meet a pre-specified accuracy. Accuracy is improved only by trial and error.

3 Expert system in scheduling

Expert systems are one of the most commercially successful branches of artificial intelligence (AI). The intelligent solutions, based on expert systems, to solve problems in scheduling are becoming more and more widespread nowadays. Especially the last decade has witnessed a growing number of manufacturing companies interested in the application of expert systems (ESs) in their plants. In this section, we present famous expert systems known in the literature and current applications in scheduling. Welbank (1983) defines an expert system as follows:

> "An expert system is a program which has a wide base of knowledge in a restricted domain, and uses complex inferential reasoning to perform tasks which a human expert could do". Also according to Ergazakis et al. (2003), "An ES is a computer system containing a well-organized body of knowledge that emulates expert problem-solving skills in a bounded domain of expertise. The system is able to achieve expert levels of problem solving performance, which would normally be achieved by a skilled human when confronted with significant problems in the domain" (Ergazakis et al. 2003).

As indicated in Fig. 3 an ES consist of three main components, which include the knowledge base, the inference engine and the user interface (Liao 2005).

Knowledge base Where the knowledge is stored in the expert system in the form of facts and rules.

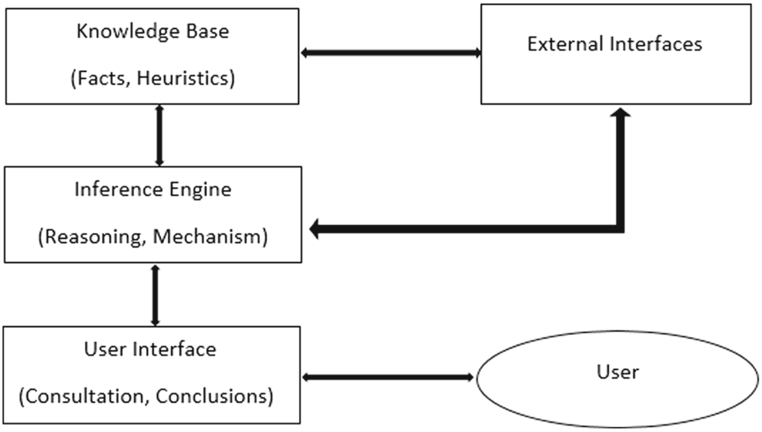

Fig. 3 Expert system's architecture (Liao 2005)

The user interface Where the user interacts with the expert system. In other words, where questions are asked, and advice is produced. As well as the advice that is output, the user interface can output the justification features of an expert system.
Inference engine This applies the facts to the rules and determines the questions to be asked of the user in the user interface and in which order to ask them.

Liao (2005) classified the ES methodologies using the following 11 categories:

1. Rule-based systems.
2. Knowledge-based systems.
3. Neural networks.
4. Fuzzy ES.
5. Object-oriented methodology.
6. Case-based reasoning.
7. System architecture.
8. Intelligent agent systems.
9. Database methodology.
10. Modelling.
11. Ontology.

Intelligent solutions based on ES are becoming more and more widespread in the industry. An ES provides a powerful and flexible means for obtaining solutions to a variety of problems that often cannot be dealt with by other methods.

Research in scheduling theory has evolved over the past 40 years and has been the subject of much significant literature. The first example and probably the earliest work in scheduling theory is intelligent scheduling and information system (ISIS) developed by Fox and Smith (1984). ISIS is a scheduling system capable of incorporating all relevant constraints in the construction of job shop schedules. It can be defined as finding a sequence of operations in order to complete an order. This is done by the assignment of time and resources to each operation. The next generation knowledge-based system was introduced by Smith and Ow (1985) and called opportunistic intelligent scheduler (OPIS) (Smith et al. 1990). In this system, the complex scheduling problem was gently broken down into simpler and relaxed problems in order to satisfy all the shop floor constraints.

PATRIARCH is a multi-level planning, scheduling, and control system that was developed for manufacturing. It incorporates artificial intelligence knowledge modeling, multi-level networking and advanced economic costing to plan on strategic forecasting and planning, master scheduling and scheduling on real-time control (Morton et al. 1984). A hybrid expert system scheduler (HESS) was developed at the University of Houston for product scheduling. The knowledge base in HESS was developed to specify what products to produce at what time, and through which processors (Deal et al. 1992).

Marsh (1985) developed a management analysis resource scheduler (MARS) to schedule resources for the space transportation system.

De Toni et al. (1996) described a production scheduler, which utilizes a hybrid push/pull approach to schedule and exploits the expert system technology in order to obtain satisfactory solutions. The scheduler is applied to a multi-stage production and inventory system, managed by make-to-order, with a large variety of incoming orders (De Toni et al. 1996).

Chen et al. (1998) built an integrated expert system called knowledge base, database, pattern recognition, artificial neural network, genetic algorithm (KDPAG), consisting of a knowledge base, a database, and pattern-recognition, ANN, and GA modules. Applications of this system give good results, as has been observed in several factories for the importance of the production of alloy steel, synthetic rubber, ceramic materials production and materials design of composite materials and ceramic semiconductors (Chen et al. 1998).

Li et al. (2000) proposed a production rescheduling expert simulation system. In this paper, four sources of production disturbances have been identified: (1) incorrect work; (2) machine breakdowns; (3) rework due to the quality problem; and (4) rush orders. These disturbances are fuzzy and random and in order to solve this ill-structured production problem, a production rescheduling expert simulation system is proposed (Li et al. 2000).

Metaxiotis et al. (2002) proposed the rule-based expert system, GENESYS (generic expert system for scheduling), for the solution of the production scheduling problem in manufacturing systems. The knowledge base of the GENESYS system includes 280 rules. The operation of this system comprises three stages. In the first stage, the user is required to respond to the questions and provide data for the parameters concerning the structure of the production system. In the second stage, the user defines the objective to be minimized. Finally, the system collects information about the particular characteristics of the production (Metaxiotis et al. 2002).

Varela et al. (2003) proposed a main contributed strategy to introduce specific knowledge into the initial population. This strategy exploits a probabilistic-based heuristic method that was designed to guide a conventional backtracking (Varela et al. 2003).

Lee et al. (2005) described a construction simulation program called CA4PRS (construction analysis for pavement rehabilitation strategies). The program was developed as a scheduling and production analysis tool for long-life pavement rehabilitation strategies (LLPRS) projects for use during the planning and design stages. CA4PRS estimates the optimized distance and duration of highway rehabilitation projects (Lee et al. 2005).

Sergio et al. (2006) compared the performance of two scheduling methods and highlighted both differences and similarities. This analysis also indicated that prioritization is a key component to determining overall performance. A fuzzy logic approach for prioritizing radar tasks in changing environmental conditions was introduced by assessing the priorities of targets and sectors of surveillance according to a set of rules, it is attempted to imitate the human decision-making process such that the resource manager can distribute the radar resources in a more effective way. Results suggest that the fuzzy approach is a valid means of evaluating the relative importance of radar tasks (Miranda et al. 2006).

Shih et al. (2007) proposed a new approach to schedule loop iterations with the irregular workload on grid environments. Based on the knowledge-based estimation of workload, the proposed method can dispatch an appropriate proportion of workload to each node for execution according to its performance (Shih et al. 2007).

Ławrynowicz (2008) proposed a methodology to support production planning and scheduling in supply net. In this approach, the production planning problem is first solved, and then the scheduling problem is considered with the constraint of the solution. The approach is implemented as a combination of expert system and genetic algorithm. The research indicates that the new system yields better results in real-life supply net than using a traditional method (Ławrynowicz 2008).

Matsumoto et al. (2009) reviewed the business processes of an automobile parts supplier. The goal of this study is to develop a knowledge-based production scheduling software with expert's technical knowledge. This paper formulates a scheduling problem by using the result of analysis, and expresses a solution methods based on expert's empirical selection rule and regards that the expert's empirical and the present state is modeled by using actual production information, particularly interview in the printing process (Matsumoto et al. 2009).

Xing et al. (2010) presented a knowledge-based ant colony optimization (KBACO) algorithm for the flexible job shop scheduling problem. KBACO algorithm provides an effective integration between ant colony optimization (ACO) model and knowledge model. In the KBACO algorithm, knowledge model learns some available knowledge from the optimization of ACO, and then applies the existing knowledge to guide the current heuristic searching of ACO. Final experimental results indicate that the proposed KBACO algorithm outperforms some published methods in the quality of schedules (Xing et al. 2010). Kırış et al. (2010) proposed a knowledge-based reactive scheduling system to answer the requirements of emergency departments (EDs). Proposed algorithm prepares schedules based on priority, arrival time, flow time and doctor load, and then minimize their waiting times (Kırış et al. 2010).

Prakash et al. (2011) addressed a complex scheduling problem in flexible manufacturing system (FMS) with a novel approach called knowledge-based genetic algorithm (KBGA). This novel approach combines KB (which uses the power of tacit and implicit expert knowledge) and inherent quality of simple genetic algorithm (SGA) for searching the optimal simultaneously (Prakash et al. 2011). Yin and Chen (2011) described the problem of dynamic scheduling with a random disturbance that taken into consideration. Through analyzing the workshop disturbance, the processing strategy and simulation procedure is proposed. On this basis, the supervisory control expert system is developed on the platform of G2 (Yin and Chen 2011).

Zarandi and Gamasaee (2012) proposed an interval type-2 fuzzy (IT2F) hybrid expert system. This system predicts the amount of tardiness where tardiness variables are represented by interval type-2 membership functions. In order to predict the future amount of tardiness for continuous casting operation in a steel company in Canada, an autoregressive moving average model is used in the consequents of the rules. This method is compared with IT2F Takagi–Sugeno–Kang method in MATLAB, multiple-regression, and two other Type-1 fuzzy methods in the literature. The results of computing the mean square error of these methods show that this method has less error and high accuracy in comparison with other methods (Zarandi and Gamasaee 2012). Karimi et al. (2012) combined variable neighborhood search (VNS) algorithm with a knowledge module and proposed knowledge-based VNS (KBVNS). The search process for finding a local or global optimum solution by VNS is totally random. To remedy this weakness of VNS, In KBVNS, the VNS part searches the solution space to find good solutions and knowledge module extracts the knowledge of good solution and feeds it back to the algorithm. This would make the search process more efficient. Computational results of the paper on different size test problems prove the efficiency of this algorithm for flexible job shop scheduling problem (Karimi et al. 2012).

Grimme et al. (2013) offered an agent-based approach to multi-criteria combinatorial optimization. It allows to flexibly combine elementary heuristics that may be optimal for corresponding single-criterion problems (Grimme et al. 2013).

Kahlon (2014) introduced a system based on concepts of fuzzy logic to schedule traffic in WiMAX networks. The approach provides dynamism to the scheduling process of WiMAX by changing weights of different queues for the weighted fair queuing scheduler. The developed system was able to allocate bandwidth to various flows on basis of instantaneous values of three variables throughput, latency and change in queue length for real and non-real time flows (Kahlon 2014).

Dong et al. (2015) investigated the resource scheduling assignment problem in cellular mobile networks by considering both the inter-cell interference and intra-cell interference simultaneously. The task of this problem is to find the minimum required bandwidth to satisfy channel demand from each cell without interference constraints violation. Also, they proposed a novel two-phase hyper-heuristic technique which integrates harmony search and a set of prior information based heuristics to solve it (Dong et al. 2015). Li et al. (2005) put forward a resource scheduling method for predictive maintenance services of equipment whose location change dynamically, aiming at eliminating potential failure, minimizing service cost and outage cost, considering the technicians' ability of different maintenance task, fault prediction information, equipment operation plan and other constraints (Li et al. 2015). Wang and Wang (2015) proposed an effective knowledge-based multi-agent evolutionary algorithm (KMEA) for solving the semiconductor final testing scheduling problem (SFTSP).

Piroozfard et al. (2016) developed a hybrid genetic algorithm for solving the non-preemptive job shop scheduling problems with the objective of minimizing makespan. In order to solve the presented problem more effectively, an operation-based representation was used to enable the construction of feasible schedules. In addition, a new knowledge-based operator was designed based on the problem's characteristics in order to use machines' idle times to improve the solution quality, and it was developed in the context of function evaluation. Furthermore, a machine based precedence preserving order-based crossover was proposed to generate the offspring. Computational results of the proposed hybrid genetic algorithm demonstrate its effectiveness (Piroozfard et al. 2016). The most important studies in the field of expert system in scheduling are summarized in Table 6.

3.1 Strengths and weaknesses of expert systems

In this subsection, a summary of the strengths and weaknesses of expert systems is presented (Mesbah 2014; Siler and Buckley 2005).

3.1.1 Strengths of expert systems

- The structure of a rule-based expert system provides an effective separation of the knowledge base from the inference engine. This makes it possible to develop different applications using the same expert system shell.
- Not forgetting the information.
- Most rule-based expert systems are capable of representing and reasoning with incomplete and uncertain knowledge.

Table 6 The most important studies in the field of expert system

Nos.	Authors	Years	Application or method	References
1	Fox and Smith	1984	Knowledge-based system for factory scheduling	Fox and Smith (1984)
2	Deal et al.	1992	Product scheduling	Deal et al. (1992)
3	De Toni et al.	1996	Artificial, intelligence-based production scheduler	De Toni et al. (1996)
4	Li et al.	2000	Production rescheduling expert simulation system	Li et al. (2000)
5	Varela et al.	2003	Evolutionary strategy for scheduling problems with bottlenecks	Varela et al. (2003)
6	Lee et al.	2005	Highway rehabilitation and reconstruction projects	Lee et al. (1907)
7	Miranda et al.	2006	Multifunction radar	Miranda et al. (2006)
8	Shih et al.	2007	Parallel loop scheduling	Shih et al. (2007)
9	Xing et al.	2010	Knowledge-based ant colony optimization for flexible job shop scheduling problems	Xing et al. (2010)
10	Kırış et al.	2010	Knowledge-based reactive scheduling system to answer the requirements of emergency departments	Kırış et al. (2010)
11	Zarandi and Gamasaee	2012	Type-2 fuzzy hybrid expert system for prediction of tardiness in scheduling of steel continuous casting process	Zarandi and Gamasaee (2012)
12	Kahlon	2014	Traffic scheduling in WiMAX networks	Kahlon (2014)
13	Dong et al.	2015	Resource scheduling assignment problem in cellular mobile networks	Dong et al. (2015)
14	Li et al.	2015	Resource scheduling method for predictive maintenance services	Li et al. (2015)
15	Wang and Wang	2015	Semiconductor final testing scheduling problem	Wang and Wang (2015)
16	Piroozfard et al.	2016	Hybrid genetic algorithm with a knowledge-based operator for solving the job shop scheduling problems	Piroozfard et al. (2016)

- Consistency: If it meets the same situation, it will make the same decision again.
- Having the ability to be used frequently by the user.
- Some expert systems can serve multi-user at a time.
- Centralizing the decision making procedure.
- Reducing the required time.
- The explanation is part of most expert systems.
- Combining multiple experts.

3.1.2 Weaknesses of expert systems

- There are some challenges in automating complex processes.
- The lack of enough ability and flexibility to be adapt against the changes of environment.
- Not having the ability to generate a creative answer when there is not available answer.
- A knowledge acquisition bottleneck results from the time-consuming and labor intensive task of building an expert system.
- Expert systems cannot generalize their knowledge by using analogy.
- Measuring the performance of an expert system is difficult because we do not know how to quantify the use of knowledge.
- Ineffective search strategy: The inference engine applies an exhaustive search through all the rules during each cycle.
- Opaque relations between rules: Although individual production rules are relatively simple and self-documented, their logical interactions within large set of rules may be opaque.
- Inability to learn: In general, rule-based expert systems do not have an ability to learn from experience. A lot of expert systems cannot automatically modify their knowledge base, or adjust existing rules or add new ones.

4 Machine learning in scheduling

Over the past two decades, machine learning has become one of the mainstays of any intelligent system. Incorporating machine learning capabilities into intelligent scheduling systems can be quite useful in elevating scheduling performance. Mitchell as the author of the book machine learning, his definition of machine learning is often quoted (Mitchell 1997):

> A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with the experience E.

The capability to improve on prior performance utilizing successes and failures from past experience is the nature of learning. In artificial intelligence, machine learning has a similar objective and has evolved to approach this goal through varied means, depending on the type of learning involved. The algorithms embedded in the scheduling system often do not yield schedules that are acceptable to the user. The inadequacy of the algorithms is based on the fact that scheduling problems are essentially intractable. It is sorely hard to extend algorithms that can provide a sensible and acceptable solution for any instance of a problem in real time.

New research initiatives are concentrating on the design and development of learning mechanisms that enable scheduling systems that are in daily use to improve their solution generation capabilities. This process requires a substantial amount of experimental work. Machine learning algorithms characteristically fall into one of two learning types: supervised or unsupervised learning (Bell 2014). A number of machine learning methods have been studied with regard to their applicability to scheduling. The methods used to learn to include a large number of different approaches. According to Quinlan the main algorithm types in the field of machine learning are case-based reasoning (CBR), neural networks and inductive learning (Quinlan 2014). Despite the ability of this method, little work has been done in applying machine learning to intelligent scheduling.

4.1 Case based reasoning in scheduling

Case-based reasoning (CBR) is a sub-field of machine learning, in which problems are solved based on past experiences. To reason from cases means to use experience made earlier in solving a certain problem to solve the current problem rather than to solve the current problem from scratch using first principles. A case usually consists of the description of a problem, a solution to the problem as well as of knowledge used in solving the problem. A case memory contains cases organized in a way to make efficient retrieval possible. In case-based reasoning, given a new problem a retrieval component retrieves the case most similar to the current problem. Using this case an adaptation component tries to generate a solution to the new problem. Bezirgan (1992) tried to outline the beginnings of a case based reasoning approach to dynamic job shop scheduling.

Sycara et al. (1995) advocated an incremental revision framework for improving schedule quality and incorporating user dynamically changing preferences through case-based reasoning.

Schmidt (1998) presented an information system supporting decision making in the area of production scheduling. The system relies on an interactive approach of problem solving which is known in the area of artificial intelligence under the name of case-based reasoning. It tries to solve new problems using results from old solved problems. While iterative solution procedures try to tackle problems from scratch, case-based reasoning takes advantage from analogies between cases. Schmidt merged case-based reasoning with the theory of scheduling to solve production planning and control problems using an interactive problem-solving framework (Schmidt 1998).

The recently proposed concept of control schemes, which refers to algorithmic schemes allowing to steer parameterized algorithms, opens up ways to refine existing algorithms in this regard and improve their effectiveness considerably. Schirmer (2000) extended this approach by integrating heuristics and case-based reasoning (CBR), an approach that has been successfully used in artificial intelligence applications. Using the resource-constrained project scheduling problem as a vehicle, Schirmer described how to devise such a CBR system, systematically analyzing the effect of several criteria on algorithmic performance (Schirmer 2000).

Priore et al. (2001) presented a scheduling approach that uses case-based reasoning (CBR), which analyzes the system's previous performance and acquires "scheduling knowledge," which determines the most suitable dispatching rule at each particular moment in time.

López (2002) introduced an approach to CBR and Constraint Satisfaction Problems (CSP) techniques integration to improve both, CBR adaptation trough CSP and CSP efficiency through the use of past experiences.

Coello and Camilo dos Santos (1998) presented the Case-Based Reasoning Real-Time Scheduler system (CBR-RTS) that integrates into a case-based reasoning framework a heuristic search component to schedule complex real-time tasks. The problem addressed involves scheduling sets of tasks with precedence, ready time and deadline constraints. CBR-RTS uses the solution of known cases to simplify and solve new problems (Coello and Camilo dos Santos 1998).

Dzeng and Lee (2004) proposed a generalized framework to represent schedule knowledge, and a computer-based system that analyzes a project schedule and offered corrective advice on potential errors by integrating case-based and rule-based reasoning.

Chang et al. (2005) presented a case study of hybrid systems with case-based reasoning and genetic algorithm for production scheduling. They presented first, the basics of case-based reasoning and production scheduling, then developed a case-based genetic algorithm

(CBGA) to deal with the single machine scheduling problem considering the release time. The objective of this case study is to minimize the total weighted completion time (Chang et al. 2005).

Chen et al. (2008) presented a method of two-stage CBR and applied to steelmaking and continuous casting dynamic scheduling system.

Pereira and Madureira (2010) proposed a learning module with the objective to permit a Multi-Agent Scheduling System to automatically select a Metaheuristic and its parameterization to use in the optimization process. They used Case-based Reasoning for the learning process, allowing the system to learn from experience, in the resolution of similar problems (Pereira and Madureira 2010).

Liu et al. (2012) introduced the design and implementation of a bus crew scheduling system (BCSS) by combining CBR and rule-based reasoning (RBR). In their work, Firstly, an inference mechanism integrating CBR and RBR is designed to obtain near-optimal solutions. Secondly, based on these near-optimal solutions, a genetic algorithm is developed to produce better solutions (Liu et al. 2012).

Pereira and Madureira (2013) presented a learning module proposal for an autonomous parameterization of Metaheuristics, integrated on a multi-agent system for the resolution of dynamic scheduling problems. The proposed learning module is inspired by autonomic computing self-optimization concept, defining that systems must continuously and proactively improve their performance. In this paper, for the learning implementation, it is used case-based reasoning, which uses previous similar data to solve new cases. In the use of case-based reasoning, it is assumed that similar cases have similar solutions (Pereira and Madureira 2013).

Kocsis et al. (2014) presented a paper entitled "Case-Based Reasoning system for mathematical modeling options, and resolution methods for production scheduling problems: Case representation, acquisition and retrieval ". The three major contributions of this paper are: (1) the proposition of an extended and a more exhaustive classification and notation scheme in order to obtain an efficient scheduling case representation, (2) a method for bibliographic analysis used to perform a deep study to fill the case base on the one hand, and to examine the topics the more or the less examined in the scheduling domain and their evolution over time on the other hand, and (3) the proposition of criteria to extract relevant past experiences during the retrieval step of the CBR (Kocsis et al. 2014).

Lim et al. (2016) presented a scheduling method for semiconductor manufacturing systems by utilizing a case-based reasoning approach that consists of modeling, case-base building, and reasoning steps.

4.1.1 Strengths and weaknesses of CBR

In this subsection, a summary of the strengths and weaknesses of case-based reasoning is presented (Kolodner and Morgan Kaufmann 2014; Kolodner and Jona 1991).

Strengths of CBR

- Learning from experiences: It does not waste effort in order to resolve a problem that is just like one it has seen in the past.
- Easier knowledge acquisition: No knowledge elicitation in order to create rules and methods.

- It allows the reasoner to propose solutions in domains that are not completely understood.
- Adaptivity: CBR displays more robustness upon encountering new problems.
- Gives the reasoner a means of evaluating solutions when no algorithmic method is available.
- It becomes more competent over time and can derive better solutions than it could with fewer experiences.
- Learning is straightforward: learning does not require a complex model.
- Avoid making the same mistakes: By remembering old mistakes, a CBR system can avoid making the same mistakes.
- CBR is intuitive: It works like the human mind.
- Scalability: Massive search is in some way avoided in CBR using Indexing.

Weaknesses of CBR

- Blind use of old cases: CBR relies on previous experiences without validating them in the new solution.
- CBR can take large storage space for all cases.
- CBR can take long processing time in order to find similar cases.
- If we need the best solution or the optimal solution, CBR may not be a good choice.
- The indexing problem: retrieval of relevant cases from memory and how to label cases so that they may be recalled when needed.

4.2 Inductive learning in scheduling

The subject of machine learning has received remarkable attention in recent years. Inductive learning is perhaps the oldest and best understood problem in this realm of science. Inductive learning can be defined as the process of inferring the description of a class from the description of individual objects of the class. A concept is a symbolic description which is true if it describes the class correctly when applied to a data case, and false otherwise (Shaw et al. 1992).

Among various learning approaches, inductive learning may be the most commonly used in real-world application domains. Inductive learning is mainly a process of inferring concept descriptions that include positive instances and exclude negative instances (Mitchell et al. 2013).

A well-known inductive learning algorithm is C4.5 (Quinlan 2014), a decision tree algorithm which uses information-theoretic measures to learn the partitions which separate examples belonging to various categories. The C4.5 algorithm uses examples in the form of vectors of attribute values and their corresponding class values and generates a decision tree.

Shaw (1989) presented an artificial intelligence method to perform manufacturing problem solving. This method was based on three AI techniques. The first was the pattern-directed inference technique to capture the dynamic nature of FMSs. The second was the nonlinear planning technique to construct schedules and assign resources. The third method was the inductive learning method to generate the pattern-directed heuristics (Shaw 1989).

Park et al. (1990) proposed a framework for incorporating machine learning into the real-time scheduling of a flexible manufacturing system and extended it to scheduling in a flexible flow system. The authors developed a Pattern Directed Scheduler (PDS) with a built-in inductive learning module for heuristic acquisition and refinement. Both simulation and inductive learning modules complemented each other, resulting in an improvement in the overall performance of the system (Park et al. 1990).

A pattern-directed method, with a built-in inductive learning module, was developed for heuristic acquisition and refinement by Shaw et al. (1992). This method enabled the scheduler to classify distinct manufacturing patterns and to generate a decision tree consisting of heuristic policies for dynamically selecting the dispatching rule appropriate for a given set of system attributes (Shaw et al. 1992).

Tsai et al. (1997) applied a fuzzy set concept to an AQR learning algorithm that is called FAQR which can induce fuzzy linguistic rules from fuzzy instances to solve the parallel loop scheduling problem. Some promising inference rules had been found and applied to infer the choice of parallel loop scheduling (Tsai et al. 1997).

Inductive learning techniques have shown appropriate results in reducing the effort for knowledge acquisition in the development of knowledge-based scheduling systems. Chen et al. (1999) proposed an auto-bias selection procedure that was capable of determining good learning biases, such as a proper feature set and a suitable learning algorithm.

Priore et al. (2003) proposed a scheduling approach that employed inductive learning and backpropagation neural networks. Using these latter techniques, and by analyzing the earlier performance of the system, "scheduling knowledge" was obtained whereby the right dispatching rule at each particular moment could be determined (Priore et al. 2003).

A generic machine learning method for regret-based biased random sampling scheme (RBRS) was presented by Gersmann and Hammer (2004). The rout-algorithm of reinforcement learning was combined with the support vector machine (SVM) to learn an appropriate value function which guided the search strategy given by RBRS. The specific properties of the SVM allowed to reduce the size of the training set (Gersmann and Hammer 2004).

Chen and Su (2008) introduced a knowledge acquisition algorithm called 'granular computing model' for imbalanced data and integrated this method into a scheduler within a simulated flexible manufacturing system (FMS) environment.

Selecting the best dispatching rule by learning from simulated data is an important issue in Inductive learning. Several researchers have used this approaches to learn rules for specific scheduling environments. For example, Malik et al. (2008a) and Russell et al. (2009) used inductive learning to generate new heuristics for block instruction scheduling, and Baykasoglu et al. (2008) used inductive learning to generate new rules for job shop scheduling.

Berral et al. (2010) proposed a framework that provided an intelligent consolidation methodology using different techniques such as turning on/off machines, power-aware consolidation algorithms, and machine learning techniques to deal with uncertain information while maximizing performance. For the machine learning approach, this paper used models learned from previous system behaviors in order to predict power consumption levels, CPU loads, and SLA timings, and improved scheduling decisions (Berral et al. 2010).

Bourenane and Mellouk (2014) described the concepts of reinforcement learning (RL) in the design of an adaptive scheduling algorithm for packets in wired networks. This research focused on the development of an algorithm of this type, called Phero-Q multi-learning, based on a cooperative multi-agent approach and a bio-inspired approach built on a theory of collective intelligence (Bourenane and Mellouk 2014).

A promising approach for an effective shop scheduling that synergizes the benefits of the combinatorial optimization, supervised learning and discrete-event simulation was presented by Shahzad and Mebarki (2016). The authors used similarity index to identify parametric and structural similarity in problem instances in order to implicitly support the learning algorithm for effective rule generation and quality index for relative ranking of the dispatching decisions. Maximum lateness was used as the scheduling objective in a job shop scheduling environment (Shahzad and Mebarki 2016).

4.2.1 Strengths and weaknesses of inductive learning

In this subsection, a summary of the strengths and weaknesses of inductive learning is presented (Dumais et al. 1998; Michalski 1983).

Strengths of inductive learning

- It is easy to construct and update.
- It can be customized to specific categories of interest to individuals.
- It allows users to smoothly tradeoff precision and recalls depending on their task.
- It is easy to validate.

Weaknesses of inductive learning

- Limited in scope and inaccurate Inferences: Inductive reasoning begins with something specific and then tries to generalize, which will go wrong more often than frequent.
- It requires massive amounts of information and only results in conclusions that are specific to situations that have the exact same characteristics as those of the observed samples.

4.3 Neural networks in scheduling

Neural Networks is a field of Artificial Intelligence (AI) where we, by inspiration from the human brain, find data structures and algorithms for learning and classification of data. Many functions that humans perform inherently fast, such as the recognition of a familiar face, proves to be a very complicated task for a computer when conventional programming methods are used. Haykin describes neural networks as an adaptive machine or more specifically (Haykin and Lippmann 1994):

> A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: Knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge.

Computer scientists have long been inspired by the human brain. McCulloch et al. (1943), developed the first conceptual model of an artificial neural network. In their paper, they explain the meaning of a neuron, a single cell living in a network of cells that receives inputs, processes those inputs, and generates an output (McCulloch and Pitts 1943). A broad class of techniques can come under this heading, but, generally, neural networks consist of layers of interconnected nodes, each node producing a non-linear function of its input. The input to a node may come from other nodes or directly from the input data. Also, some nodes are identified with the output of the network. The complete network, therefore, represents a very complex set of interdependencies which may incorporate any degree of nonlinearity, allowing very general functions to be modeled (Anderson 1995).

One of the key elements of a neural network is its capability to learn. A neural network is not just a complex system, but a complex adaptive system, meaning it can change its internal structure based on the information flowing through it. Typically, this is achieved through the adjusting of weights. In the diagram below, each line represents a connection between two neurons and indicates the pathway for the flow of information. Each connection has a weight, a number that controls the signal between the two neurons (Fig. 4).

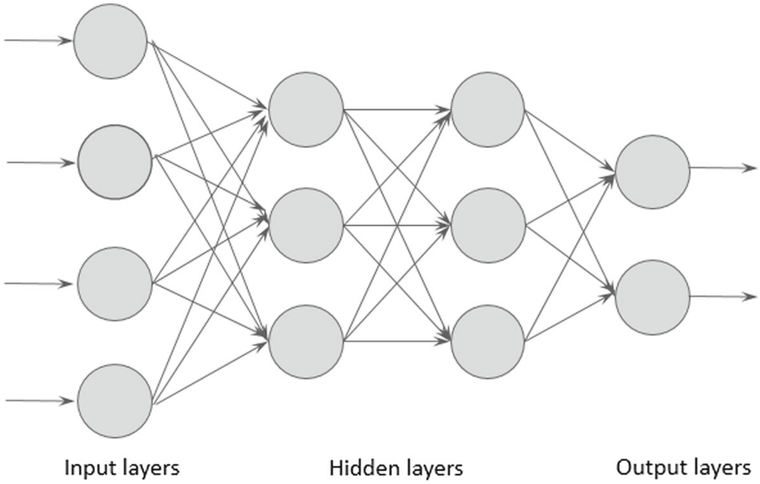

Fig. 4 Neural network's architecture (Haykin and Lippmann 1994)

Simon and Takefuji (1988) presented an integer linear programming neural network (ILPNN) based on a modified Tank and Hopfield neural network model to solve job shop scheduling. The constraints of the job shop problem were formulated as a set of integer linear equations. The cost function for minimization was the total starting times of all jobs subject to precedence constraints (Simon and Takefuji 1988).

A hybrid architecture that integrated artificial neural networks and knowledge-based expert systems to generate solutions for the real-time scheduling of flexible manufacturing systems was described by Rabelo et al. (1990). The artificial neural networks performed pattern recognition and, due to their inherent characteristics, supported the implementation of automated knowledge acquisition and refinement schemes through a feedback mechanism (Rabelo et al. 1990).

A scheduling problem for minimizing the total actual flow time was solved using the gaussian machine model which is one of the stochastic neural network models in the work of Arizono et al. (1992).

Toure et al. (1993) applied three different schemes of ANN's to the FMS scheduling problem. These schemes include relaxation-based networks, competitive-based schemes and adaptive pattern recognition scheduling (Toure et al. 1993).

Scheduling problems with resource allocation constraints generally belong to the large class of NP-complete problems. An important group of such problems concerns Timetable Construction (TC) for people and tools. Pellerin and Hérault (1994) proposed an efficient approach to TC using neural networks with Backward Lateral Inhibitions (BLI) for constraints management.

A hybrid artificial neural network-differential dynamic programming (ANN-DDP) method for the scheduling of short-term hydro generation was developed by Liang and Hsu (1995). In the proposed method, the DDP procedures were performed offline on historical load data. The results were compiled and valuable information was obtained by using ANN algorithms. The DDP algorithm was then performed online according to the obtained information to give the hydro generation schedule for the forecasted load (Liang and Hsu 1995). Willems and Brandts (1995) presented an enhanced neural network architecture for job shop scheduling in which the general rules of thumb for job shop scheduling had been incorporated as a local optimization criterion. Implementation of the rules of thumb, by adaptation of the network architecture, resulted in a network that actually incorporated the optimization criterion, enabling parallel hardware implementation (Willems and Brandts 1995).

Liu and Dong (1996) presented a new algorithm for job shop scheduling problems. This algorithm consisted of three stages. First, computer simulation techniques were used to evaluate the efficiency of heuristic rules in different scheduling situations. Second, the simulation results were used to train a neural network in order to capture the knowledge. Finally, the trained neural network was used as a dispatching rule selector in the real-time scheduling process (Liu and Dong 1996).

Li et al. (1997) applied neural network learning techniques and a decision tree method to obtain scheduling knowledge for flexible manufacturing systems. This paper, first configured a typical flexible manufacturing system and defined a set of decision parameters along with a set of system performance evaluation criteria. An on-line scheduling and control system in batch process management consists of three modules. Action strategy generation module (ASGM) is the key kernel of this system (Li et al. 1997).

A complicated job scheduling problem of a multiprocessor with multi-process instance under execution time limitation process migration inhibited and bounded available resource constraints was presented by Chen and Huang (1998). An energy-based equation was developed first whose structure depended on precise constraints and acceptable solutions using an extended 3D Hopfield neural network (HNN) and the normalized mean field annealing (MFA) technique; a variant of mean field annealing was conducted as well. A modified cooling procedure to accelerate a reaching equilibrium for normalized mean field annealing was applied to this study (Chen and Huang 1998).

By combining neural network with lagrangian relaxation for constraint handling, a novel lagrangian relaxation neural network (LRNN) for job shop scheduling was developed by Luh et al. (1999).

A hybrid approach involving neural networks and genetic algorithm (GA) was proposed by Yu and Liang (2001) to solve a practical production scheduling problem with processing constraints. The GA was used for optimization of sequence and a neural network (NN) was used for optimization of operation start times with a fixed sequence (Yu and Liang 2001).

An attribute selection algorithm based on the weights of neural networks to measure the importance of system attributes in a neural network-based adaptive scheduling (NNAS) system was proposed by Shine and Su (2002).

Wang et al. (2003) designed a neural network to solve the flexible flow shop problem. A key feature of this neural network was the integration of problem structure and heuristic information in the network structure and solution (Wang et al. 2003).

An approach for scheduling under a common due date on parallel unrelated machine problems based on artificial neural network was presented by Hamad et al. (2003). The objective was to allocate and sequence the jobs on the machines so that the total cost was minimized (Hamad et al. 2003).

Hao et al. (2004) presented and evaluated a neural network model for solving a typical personnel-scheduling problem, i.e. an airport ground staff rostering problem. Wu et al. (1994) presented a neural network for scheduling and allocation in VLSI design.

Tang et al. (2005) proposed a neural network model and algorithm to solve the dynamic hybrid flow shop scheduling problem.

Agarwal et al. (2006) proposed an augmented neural-network approach, which allows the integration of greedy as well as non-greedy heuristics (AugNN-GNG), to give improved solutions in a small number of iterations. The problem they addressed is that of minimizing the makespan of n tasks on m identical machines (or processors), where tasks are non-preemptive and follow a precedence order. The proposed approach in this paper exploits the observation that a non-greedy search heuristic often finds better solutions than do their greedy counterparts. They hypothesized that combinations of non-greedy and greedy heuristics when integrated with an augmented neural-network approach can lead to better solutions than can either one alone (Agarwal et al. 2006).

Shen and Wang (2008) described fuzzy Hopfield Neural Network (FHNN) technique to solve the TDMA (time division multiple access) broadcast scheduling problem in wireless sensor networks (WSN). They formulated it as discrete energy minimization problem and map it into Hopfield neural network with the fuzzy c-means strategy to find the TDMA schedule for nodes in a communication network (Shen and Wang 2008).

Akyol and Mirac Bayhan (2008) presented a paper entitled "Multi-machine earliness and tardiness scheduling problem: an interconnected neural network approach ". In this paper, the objective is to propose a dynamical gradient neural network, which employs a penalty function approach with time-varying coefficients for the solution of the problem which is known to be NP-hard. After the appropriate energy function was constructed, the dynamics are defined by steepest gradient descent on the energy function. The proposed neural network system is composed of two maximum neural networks, three piecewise linear and one log-sigmoid network all of which interact with each other (Akyol and Mirac Bayhan 2008).

Xizheng and Yaonan (2009) described the broadcast scheduling problem (BSP) that is aimed to schedule each node in a different slot of fixed length frame at least once, and the objective of BSP is to seek for the optimal feasible solution, which has the shortest length of frame slots, as well as the maximum node transmission.

Yang et al. (2010) presented an improved constraint satisfaction adaptive neural network for job shop scheduling problems. In this paper, the neural network is constructed based on the constraint conditions of a job shop scheduling problem. Its structure and neuron connections can change adaptively according to the real-time constraint satisfaction situations that arise during the solving process. Several heuristics are also integrated within the neural network to enhance its convergence, accelerate its convergence, and improve the quality of the solutions produced (Yang et al. 2010).

Chen (2011) introduced a simplified two-dimensional Hopfield-type neural network using competitive rule for solving three-dimensional multiprocessor real-time scheduling problems.

Azadeh et al. (2012a) proposed an algorithm based on computer simulation and artificial neural networks to select the optimal dispatching rule for each machine from a set of rules in order to minimize the makespan in stochastic job shop scheduling problems (SJSSPs). In another paper, Azadeh et al. (2012a) presented an integrated computer simulation and Artificial Neural Network (ANN) algorithm for a stochastic Two-Stage Assembly Flow shop Scheduling Problem (TSAFSP) with setup times under a weighted sum of makespan and mean completion time (MCT) criteria, known as bi-criteria.

Kechadi et al. (2013) focused on modeling the manufacturing application as a cyclic job shop problem and developed an efficient neural network approach to minimize the cycle time of a schedule. Young et al. (2013) proposed a gain scheduling approach by neural network to force control of the electric vehicle wheels. To approximate to the reality in simulation, they utilized the traction force database of the motor, called the current-RPM-torque database, instead of the slip ratio measurements (Young et al. 2013).

Simankina and Popova (2014) discussed the application of mathematical simulation for planning the timing of repair of building structures according to their degree of physical deterioration.

Grzonka et al. (2015) defined a novel model of security-driven grid schedulers supported by an artificial neural network. ANN module monitors the schedule executions and learns about secure task-machine mappings from the observed machine failures. Then, the metaheuristic grid schedulers are supported by the ANN module through the integration of the sub-optimal schedules generated by the neural network, with the genetic populations of the schedules (Grzonka et al. 2015).

Tripathy and Dash (2015) introduced three novel approaches for the task scheduling problem using Directed Search Optimization (DSO). In their work, task scheduling is framed as an optimization problem and solved by DSO. Next, this paper makes use of DSO as a training algorithm to train (a) a three-layer ANN and then (b) Radial Basis Function Neural Networks (RBFNN) (Tripathy and Dash 2015). In another paper, Tripathy and Dash (2015) designed novel methods for neural network and RBFNN training using Shuffled Frog-Leaping Algorithm (SFLA). In this paper, the scheduling problem is structured as a problem of optimization and solved by SFLA. Next, this paper makes use of SFLA trained artificial neural network and RBFNN for the problem of task scheduling (Tripathy et al. 2015).

Ezugwu et al. (2016) proposed a neural network-based multi-agent resource selection technique capable of mimicking the services of an expert user. In addition, to cope with the geographical distribution of the underlying system, they employed a multi-agent coordination mechanism. In this paper, the proposed neural network-based scheduling framework combined with the multi-agent intelligence is a unique approach to efficiently deal with the resource selection problem (Ezugwu et al. 2016). Tahir and Asghar Saqib (2016) presented a case study of Pakistan's power system where the generated power, the load demand, frequency deviation, and the load shed during a 24-h duration have been provided. In this paper, the data have been analyzed using two techniques; the conventional artificial neural network by implementing a feed forward back propagation model and the Bootstrap aggregating or bagging algorithm (Tahir and Asghar Saqib 2016). The most important studies in the field of machine learning in scheduling are summarized in Table 7.

4.3.1 Strengths and weaknesses of neural networks

In this subsection, a summary of the strengths and weaknesses of neural networks is presented (Jain and Martin 1999; Akyol and Mirac 2007; Svozil et al. 1997).

Strengths of neural networks

- Neural net-based solutions do not use mathematical modeling of the system. Neural nets learn system behavior using system input–output data.
- Neural nets have a simple mechanism to be utilized in scheduling problems, even if the training is slow, a trained network can produce its output very rapidly.
- Neural nets have better generalization capabilities over competing machine learning tools to capture the complex relationship between the input and output variables of the considered scheduling problem.
- Neural nets have great learning and generalization capabilities that enable them to more effectively address nonlinear, time-variant problems, even under noisy conditions.
- Neural nets can develop solutions to meet a pre-specified accuracy.
- Neural nets are applicable to different kinds of combinatorial optimization problems in various disciplines.

Table 7 The most important studies in machine learning in scheduling

Nos.	Authors	Years	Method	References	Nos.
1	Bezirgan	1992	CBR	Dynamic job shop scheduling	Bezirgan (1992)
2	Schirmer	2000	CBR	Production planning and control	Schirmer (2000)
3	Coello and Camilo dos Santos	2003	CBR	Complex real-time tasks scheduling	Coello and Camilo dos Santos (1998)
4	Chang et al.	2005	CBR	Production scheduling	Chang et al. (2005)
5	Chen et al.	2008	CBR	Steelmaking and continuous casting dynamic scheduling system	Chen et al. (2008)
6	Liu et al.	2012	CBR	Bus crew scheduling	Liu et al. (2012)
7	Kocsis et al.	2014	CBR	Mathematical modelling options	Pereira and Madureira 2013)
8	Lim et al.	2016	CBR	Semiconductor manufacturing facilities	Lim et al. (2016)
9	Shaw	1989	IL	Flexible manufacturing problem	Shaw (1989)
10	Tsai et al.	1997	IL	Parallel loop scheduling	Tsai et al. (1997)
11	Priore et al.	2003	IL	Dynamic scheduling of flexible manufacturing system	Priore et al. (2003)
12	Chen and Su	2008	IL	Simulated flexible manufacturing system	Chen and Su (2008)
13	Malik et al.	2008	IL	Basic block instruction scheduling	Malik et al. (2008)
14	Russell et al.	2009	IL	Superblock instruction scheduling	Russell et al. (2009)
15	Bourenane and Mellouk	2014	IL	Packet scheduling in communication networks	Bourenane and Mellouk2014
16	Shahzad and Mebarki	2016	IL	Learning dispatching rules for scheduling	Shahzad and Mebarki (2016)
17	Simon and Takefuji	1988	NN	Job shop scheduling	Simon and Takefuji (1988)
18	Rabelo et al.	1990	NN	Flexible manufacturing systems	Rabelo et al. (1990)
19	Pellerin and Hérault	1994	NN	Time-table construction	Pellerin and Hérault (1994)
20	Liang and Hsu	1995	NN	Short-term hydro scheduling	Liang and Hsu (1995)
21	Chen and Huang	1998	NN	Multi-constraint task scheduling in multi-processor system	Chen and Huang (1998)
22	Shine and Su	2002	NN	Attribute selection	Shine and Su (2002)
23	Wang et al.	2003	NN	Flexible flow shop scheduling	Wang et al. (2003)

Table 7 continued

Nos.	Authors	Years	Method	References	Nos.
24	Hao et al.	2004	NN	Personnel scheduling	Hao et al. (2004)
25	Tang et al.	2005	NN	Dynamic hybrid flow shop scheduling	Tang et al. (2005)
26	Agarwal et al.	2006	NN	Augmented neural-network approach for scheduling problems	Agarwal et al. (2006)
27	Shen and Wang	2008	NN	Broadcast scheduling in wireless sensor networks	Shen and Wang (2008)
28	Yang et al.	2010	NN	Job shop scheduling	Yang et al. (2010)
29	Chen	2011	NN	Three-dimensional multiprocessor real-time scheduling	Chen (2011)
30	Azadeh et al.	2012	NN	Stochastic job shop scheduling	Azadeh et al. (2012b)
31	Young et al.	2013	NN	Force control of the electric vehicle wheels	Young et al. (2013)
32	Simankina and Popova	2014	NN	Building construction scheduling	Simankina and Popova (2014)
33	Tripathy et al.	2015	NN	Dynamic task scheduling	Tripathy and Dash (2015)
34	Ezugwu et al.	2016	NN	Resource selection problem	Ezugwu et al. (2016)
35	Tahir and Asghar Saqib	2016	NN	Electrical power system	Tahir and Asghar Saqib (2016)

In this table CBR means Case Based Reasoning, IL means Inductive Learning and NN is equal to Neural Networks

Weaknesses of neural networks

- Black box nature: It means that we do not know how and why the neural networks came up with a specific output.
- Neural networks are more computationally expensive than traditional algorithms.
- It is difficult to determine the appropriate values of the penalty parameters, network parameters, and structure of a neural net to solve a given problem.
- Generating a training set is time-consuming.
- The adequacy of the training set has a great effect on generalization ability.
- The performance of neural nets can degrade because of overlearning.
- Neural nets do not scale well.
- Neural nets get easily trapped in local minimum states.
- Neural nets may not converge to good quality solutions.
- The ways of incorporating constraints into the energy function affect the quality of the solution.
- The termination criteria affect the quality of the results.

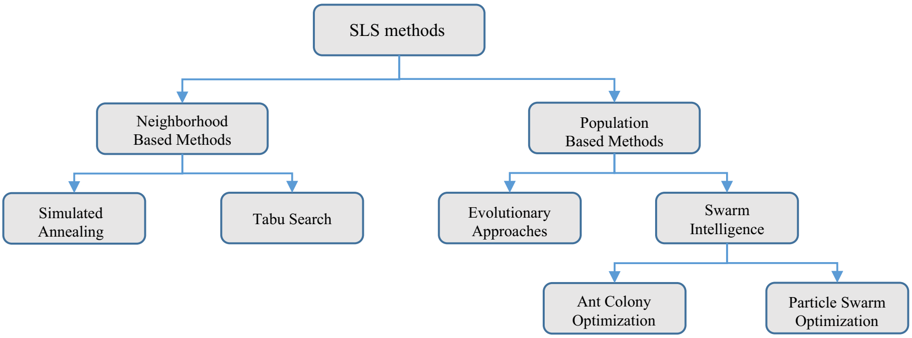

Fig. 5 Classification of SLS methods (Vallada et al. 2008)

5 Stochastic local search optimization algorithms in scheduling

In the last 20 years, a new kind of approximate optimization method has emerged, which basically tries to combine heuristic methods with higher level frameworks aimed at effectively exploring a search space. These methods are nowadays generally called Stochastic Local Search (SLS) methods.

SLS methods are general methods that guide the search through the solution space, using as surrogate algorithms some form of heuristics and usually local search. Starting from an initial solution built by some heuristic, SLS methods improve it iteratively until a stopping criterion is met (Vallada et al. 2008). Approximation techniques attracted a lot of interest in recent time regardless of many critics due to the usual lack of mathematical basis for convergence and optimality. Due to the complexity of some scheduling problems, using exact methods to solve them is impracticable for instances of more than a few jobs and/or machines. SLS methods have been successfully used to solve a wide range of scheduling problems. The broad classification of SLS methods is shown in Fig. 5 (Vallada et al. 2008).

5.1 Simulated annealing

In the early 1980s, Kirkpatrick et al. introduced the concepts of annealing in combinatorial optimization. Originally these concepts were greatly inspired by an analogy between the physical annealing process of solids and the problem of solving large combinatorial optimization problems. The algorithm initializes by generating an initial random solution. After that, the adjoining solution is being generated and these two solutions will be evaluated by an objective function. If the cost of the neighbor is lower than the cost of the initial solution and lowers the energy of the system, the neighbor will be accepted as an improved solution. As for a non-improving solution, it will gradually be accepted with a probability value given by a probability function (Teoh et al. 2015). Its ease of implementation and convergence properties and its use of hill-climbing moves to escape local optima have made it a popular technique over the past two decades.

The problem of scheduling jobs in a flow shop was considered by Osman and Potts (1989). The job processing order must be the same on each machine and the objective was to minimize the maximum completion time. Simulated annealing was proposed as a heuristic to obtain approximate solutions (Osman and Potts 1989).

Ogbu and Smith (1990) presented an approach for solving the n-job, m-machine flow shop scheduling problem with minimum completion time using both heuristic and randomly generated solutions as initial seeds to a simulated annealing optimization process.

The application of a simulated annealing heuristic to an NP-complete cyclic staff-scheduling problem was presented by Brusco and Jacobs (1993). It was designed for use in a continuously operating scheduling environment with the objective of minimizing the number of employees necessary to satisfy forecast demand (Brusco and Jacobs 1993).

Ishibuchi et al. (1995) proposed two simulated annealing algorithms with a modified generation mechanism and applied to the m-machine and n-job flow shop sequencing problem with the objective of minimizing the makespan. The generation mechanism was modified in order to obtain a robust performance with respect to the choice of a cooling schedule (Ishibuchi et al. 1995).

A simulated annealing algorithm for resource constrained project scheduling problems with the objective of minimizing makespan was proposed by Cho and Kim (1997). In the search algorithm, a solution was represented with a priority list, a vector of numbers each of which denoted the priority of each activity (Cho and Kim 1997).

Steinhöfel et al. (1999) proposed two simulated annealing-based algorithms for the classical, general job shop scheduling problem where the objective was to minimize the makespan.

The resource-constrained project scheduling problem with multiple execution modes for each activity and the makespan as the minimization criterion was considered by Józefowska et al. (2001). Furthermore, a simulated annealing approach to solve this problem was presented (Józefowska et al. 2001).

Mika et al. (2005) considered the multi-mode resource-constrained project scheduling problem with discounted cash flows. A project was represented by an activity-on-node (AoN) network. A positive cash flow was associated with each activity. The objective was to maximize the net present value of all cash flows of the project. SLS methods: simulated annealing and tabu search, were proposed to solve this strongly NP-hard problem (Mika et al. 2005).

The job shop scheduling problem was studied by Suresh and Mohanasundaram (2006) with the objectives of minimizing the makespan and the mean flow time of jobs. The simultaneous consideration of these objectives was the multi-objective optimization problem under study. An SLS procedure based on the simulated annealing algorithm called Pareto archived simulated annealing (PASA) was proposed to discover non-dominated solution sets for the job shop scheduling problems (Suresh and Mohanasundaram 2006).

Lee et al. (2007) discussed the scheduling problem of two-transtainer systems. The problem was to schedule two transtainers which serve the loading operations of one quay crane at two different container blocks so as to minimize the total loading time at stack area. A mathematical model was provided to formulate the problem and a simulated annealing (SA) algorithm was developed to solve the proposed model (Lee et al. 2007).

An integer linear programming (ILP) model was presented for the problem to minimize the makespan, which considers intercellular moved and non-consecutive multiple processing of parts on a machine A particle swarm optimization algorithm with and without a proposed local search was developed by Bank et al. (2012) to determine a job sequence with minimization of the total tardiness criterion. Furthermore, a simulated annealing was proposed to solve the problem (Bank et al. 2012).

The internet of things (IoT) and cloud computing are two novel paradigms both rapidly evolving in their particular areas of application. Moschakis and Karatza (2015) evaluated the application of simulated annealing in a multi-cloud system serving a workload of processes with low parallelism but with high arrival rates and highly variant run-times. A discrete event simulator was used in order to assess both the performance and the cost of the system

(Moschakis and Karatza 2015). The most important studies in the field of simulated annealing are summarized in Table 8.

5.1.1 Strengths and weaknesses of simulated annealing

In this subsection, a summary of the strengths and weaknesses of simulated annealing is presented (Coello et al. 2007; Laarhoven and Peter 1987; Czyzżak and Jaszkiewicz 1998).

Strengths of simulated annealing

- The existence of convergence proofs for this method.
- The suitability of simulated annealing for parallel implementation when efficiency is emphasized.
- An ability to avoid becoming trapped in local minima. The algorithm employs a random search which not only accepts changes that decrease the objective function, but also some changes that increase it.
- Simulated annealing can deal with highly nonlinear models, chaotic and noisy data and many constraints.
- Its flexibility and its ability to approach global optimality.
- The algorithm is quite versatile since it does not rely on any restrictive properties of the model.
- Weaknesses of simulated annealing.
- There is a clear tradeoff between the quality of the solutions and the time required to compute them.
- The tailoring work required to account for different classes of constraints and to fine-tune the parameters of the algorithm can be rather delicate.
- The precision of the numbers used in implementation is of SA can have a significant effect on the quality of the outcome.
- The difficulty in defining a good cooling schedule.
- It can require much tuning of the initial temperature and annealing schedule.
- For problems where there are few local minima, SA is overkill.
- The method cannot tell whether it has found an optimal solution. Some other method (e.g. branch and bound) is required to do this.

5.2 Tabu search

Building upon some of his previous work, Glover proposed in 1986 a new approach, which he called Tabu Search, to allow local search methods to dominate local optima. It uses the information gathered pending the iterations to make the search process more effective. As in the case of SA, it also accepts non-improving solutions to move out of local optima. Nevertheless, TS algorithm searches the whole neighborhood deterministically unlike SA that employs a random search. The distinguishing feature of TS is the use of a short-term memory that prevents formerly visited solutions from being accepted again. It speeds up the attainment of the optimum solution (Gogna and Tayal 2013).

Tabu Search (TS), created by Glover in 1986, is a very powerful SLS method that has shown its efficiency when solving various combinatorial optimization problems. Tabu Search guides a local heuristic search procedure to explore the solution space beyond local optimality.

Table 8 The most important studies in the field of simulated annealing

Nos.	Authors	Years	Application or method	References
1	Osman and Potts	1989	Permutation flow shop scheduling	Osman and Potts (1989)
2	Ogbu and Smith	1990	The $n/m/C_{max}$ flow shop problem	Ogbu and Smith (1990)
3	Ku and Karimi	1991	Serial multi-product process with a single batch unit	Ku and Karimi (1991)
4	Brusco and Jacobs	1993	Cyclic staff-scheduling problem	Brusco and Jacobs (1993)
5	Ishibuchi et al.	1995	Flow shop sequencing problem	Ishibuchi et al. (1995)
6	Cho and Kim	1997	Resource constrained project scheduling problems	Cho and Kim (1997)
7	Steinhöfel et al.	1999	General job shop scheduling problem	Steinhöfel et al. (1999)
8	Józefowska et al.	2001	Resource-constrained project scheduling problem	Józefowska et al. (2001)
9	Kim et al.	2002	Unrelated parallel machines with sequence-dependent setup times	Kim et al. (2002)
10	Aydin and Fogarty	2004	Job shop scheduling	Aydin and Fogarty (2004)
11	Mika et al.	2005	Multi-mode resource-constrained project scheduling problem	Mika et al. (2005)
12	Suresh and Mohanasun-daram	2006	Job shop scheduling problem	Suresh and Mohanasun-daram (2006)
13	Lee et al.	2007	Scheduling of two-transtainer systems for loading outbound containers	Lee et al. (2007)
14	Kalashnikov et al.	2008	Multiprocessor scheduling	Kalashnikov and Kostenko (2008)
15	Jin et al.	2009	Single machine scheduling problems with family setups	Jin et al. (2009)
16	Zhang et al.	2010	Hybrid simulated annealing algorithm based on an immune mechanism	Zhang and Wu (2010)
17	Wang et al.	2011	Hybrid flow shop scheduling	Wang et al. (2011)
18	Wu et al.	2011	Single-machine scheduling problem with learning and unequal job release times	Wu et al. (2011)
19	Bank et al.	2012	Permutation flow shop scheduling problem with deteriorating jobs	Bank et al. (2012)
20	Damodaran et al.	2012	Parallel batch processing machines with unequal job ready times	Damodaran and Vélez-Gallego (2012)

Table 8 continued

Nos.	Authors	Years	Application or method	References
21	Jolai et al.	2013	No-wait two-stage flexible flow shop scheduling problem	Jolai et al. (2013)
22	Kaplan and Rabadi	2013	Aerial refueling parallel machine scheduling problem	Kaplan and Rabadi (2013)
23	Chan et al.	2013	Hybrid Tabu sample-sort simulated annealing approach	Chan et al. (2013)
24	Abdullah and Othman	2014	Cost-based multi-quality of service job scheduling	Abdullah and Othman (2014)
25	Haridass et al.	2014	Log truck scheduling	Haridass et al. (2014)
26	Shivasankaran et al.	2014	Hybrid non-dominated sorting simulated annealing algorithm	Shivasankaran et al. (2014)
27	Moschakis and Karatza	2015	Multi-criteria scheduling on heterogeneous interlinked clouds	Moschakis and Karatza (2015)
28	Lin and Ying	2015	Multi-point simulated annealing heuristic	Lin and Ying (2015)
29	Shivasankaran et al.	2015	Hybrid sorting immune simulated annealing algorithm	Shivasankaran et al. (2015)
30	Bożejko et al.	2015	Cyclic flexible job shop scheduling problem	Bożejko et al. (2015)
31	Bilolikar et al.	2016	Multi-mode resource constrained project scheduling	Bilolikar et al. (2016)
32	Chen et al.	2016	Scheduling systems for TFT-LCD colour filter fabs	Chen et al. (2016)
33	Harmanani and Ghosn	2016	Non-preemptive open shop scheduling problem	Harmanani and Ghosn (2016)
34	Liu et al.	2016	Hybrid simulated annealing	Liu and Wang (2016)

Glover and Laguna (1989) explored the integrated Artificial Intelligence/Operations Research approach known as target analysis in application to tabu search. In this paper, they presented the process involved in embedding the target analysis methodology in a tabu search method which is tailored for the solution of a class of single machine scheduling problems (Glover and Laguna 1989).

Costa (1995) presented a new evolutionary procedure for solving general optimization problems that combines efficiently the mechanisms of genetic algorithms and tabu search. Costa discussed an adaptation of this search principle to the National Hockey League (NHL) problem (Costa 1995).

França et al. (1996) proposed a new three-phase heuristic for solving the problem of scheduling n jobs on m identical parallel processors with the objective of minimizing the total execution time. An initial phase constructs a starting solution which is improved, in a second phase, by means of a tabu search method. A final phase follows attempting a further improvement in the current solution (França et al. 1996).

Armentano and Ronconi (1999) presented a paper entitled "Tabu search for total tardiness minimization in flow shop scheduling problems". They first analyzed the behavior of solutions for small problems for different due date scenarios. Then proposed a tabu search-based heuristic as a method to explore the solution space and evaluated diversification, intensification, and neighborhood restriction strategies (Armentano and Ronconi 1999).

Pezzella and Merelli (2000) presented a computationally effective heuristic method for solving the minimum makespan problem of job shop scheduling. The proposed local search method is based on a tabu search technique and on the shifting bottleneck procedure used to generate the initial solution and to refine the next-current solutions (Pezzella and Merelli 2000).

Al-Turki et al. (2001) developed a tabu search-based solution procedure designed specifically for a certain class of single-machine scheduling problems with a non-regular performance measure. The performance of the developed algorithm is tested for solving the variance minimization problem (Al-Turki et al. 2001).

Chen et al. (2007) presented an integrated model to schedule the equipment. The objective is to minimize the makespan, or the time it takes to serve a given set of ships. They formulated the problem as a hybrid flow shop scheduling problem with precedence and blocking constraints (*HFSS-B*) and proposed a tabu search algorithm to solve this problem (Chen et al. 2007).

Peng et al. (2015) presented an algorithm that incorporates a tabu search procedure into the framework of path relinking to generate solutions to the job shop scheduling problem. This tabu search/path relinking (TS/PR) algorithm comprises several distinguishing features, such as a specific relinking procedure to effectively construct a path linking the initiating solution and the guiding solution, and a reference solution determination mechanism based on two kinds of improvement methods (Peng et al. 2015). Table 9 summarizes the researches have been done in scheduling with tabu (taboo) search.

5.2.1 Strengths and weaknesses of tabu search

In this subsection, a summary of the strengths and weaknesses of tabu search is presented (Coello et al. 2007; Glover and Kochenberger 2006; Marett and Wright 1996).

Strengths of tabu search

- It allows non-improving solution to be accepted in order to escape from a local optimum.
- The use of the tabu list.
- Can be applied to both discrete and continuous solution spaces.
- For larger and more difficult problems (scheduling, quadratic assignment, and vehicle routing), tabu search obtains solutions that rival and often surpass the best solutions previously found by other approaches.
- A semi-deterministic nature as it acts both as a local and global search method.

Weaknesses of tabu search

- Too many parameters to be determined.
- The number of iterations could be very large.

Table 9 Scheduling with tabu (taboo) search (TS)

Nos.	Authors	Years	Application or method	References
1	Glover and Laguna	1989	Target analysis to improve a tabu search method for machine scheduling	Glover and Laguna (1989)
2	Morton and Ramnath	1992	Tabu/beam search for scheduling very large dynamic job shops	Morton and Ramnath (1992)
3	Laguna and Glover	1993	Integrating target analysis and tabu search for improved scheduling systems	Laguna and Glover (1993)
4	Hübscher and Glover	1994	Multiprocessor scheduling	Hübscher and Glover (1994)
5	Costa	1995	An evolutionary tabu search algorithm and the NHL scheduling problem	Costa (1995)
6	França et al.	1996	Multiprocessor scheduling problem with sequence dependent setup times	França et al. (1996)
7	Brandao and Mercer	1997	Multi-trip vehicle routing and scheduling problem	Brandao and Mercer (1997)
8	Dowsland	1998	Nurse scheduling with tabu search and strategic oscillation	Dowsland (1998)
9	Lopez et al.	1998	Hot strip mill production scheduling problem	Lopez et al. (1998)
10	Armentano and Ronconi	1999	Flow shop scheduling problem	Armentano and Ronconi (1999)
11	Pezzella and Merelli	2000	Tabu search method guided by shifting bottleneck	Pezzella and Merelli (2000)
12	Al-Turki et al.	2001	Single-machine scheduling problem	Al-Turki et al. (2001)
13	Alvarez-Valdes et al.	2002	Course scheduling system	Alvarez-Valdes et al. (2002)
14	Liaw	2003	Two-machine preemptive open shop scheduling problem	Liaw (2003)
15	Baykasoğlu and Sönmez	2004	Multi-objective flexible job shop scheduling problems	Baykasoğlu and AlI (2004)
16	Mika et al.	2005	Multi-mode resource-constrained project scheduling	Mika et al. (2005)
17	Choobineh et al.	2006	Single-machine scheduling problem with sequence-dependent setup times	Choobineh et al. (2006)

Table 9 continued

Nos.	Authors	Years	Application or method	References
18	Chen et al.	2007	Integrated scheduling problem of container handling systems in a maritime terminal	Chen et al. (2007)
19	Mika et al.	2008	Multi-mode resource-constrained project scheduling with schedule-dependent setup times	Mika et al. (2008)
20	He et al.	2009	Multi-mode project payment scheduling	He et al. (2009)
21	Xu et al.	2010	Scheduling jobs with controllable processing times on a single machine to meet due dates	Xu et al. (2010)
22	Li et al.	2011	Hybrid tabu search algorithm with a neighborhood structure	Li et al. (2011)
23	Vilcot and Billaut	2011	Multi-criteria flexible job shop scheduling problem	Vilcot and Billaut (2011)
24	Meeran and Morshed	2012	Hybrid genetic tabu search algorithm for solving job shop scheduling problems	Meeran and Morshed (2012)
25	Zhang et al.	2012	Flexible job shop scheduling with transportation constraints and bounded processing times	Zhang et al. (2012)
26	Gao et al.	2013	Distributed permutation flow shop scheduling problem	Gao et al. (2013)
27	Ponsich and Coello	2013	Hybrid differential evolution tabu search algorithm for job shop scheduling problems	Ponsich et al. (2013)
28	Jia and Hu	2014	Path-relinking Tabu search for the multi-objective flexible job shop scheduling problem	Jia and Zhi-Hua (2014)
29	Ahani and Asyabani	2014	No-wait job shop scheduling problem	Ahani and Asyabani (2014)
30	Peng et al.	2015	Tabu search/path relinking algorithm to solve the job shop scheduling problem	Peng et al. (2015)
31	Sels et al.	2015	Hybrid tabu search and a truncated branch-and-bound for the unrelated parallel machine	Sels et al. (2015)
32	Soykan and Rabadi	2016	Multiple runway aircraft scheduling problem	Soykan et al. (2016)

- Global optimum may not be found, depends on parameter settings.
- It makes heavily and intelligently use of both short-term and long-term memory.
- No theory has yet been formulated to support TS and its convergence behavior.
- Domain-specific knowledge is needed for selection for tabus and aspiration criteria.
- Efficient data structure must be used for tabu list manipulation.
- Its use in continuous search spaces has not been common due to the difficulties of performing neighborhood movements in continuous search spaces.
- It becomes harder to design a good tabu search method as the number of objective functions increases.

5.3 Particle swarm optimization (PSO)

Particle swarm optimization was first proposed by Kennedy and Eberhart (1995). PSO is a swarm intelligence SLS method inspired by the group behavior of animals, e.g. bird flocks or fish schools. Similarly, to genetic algorithms (GAs), it is a population-based method which is iteratively modified until a termination criterion is satisfied. The PSO involves a number of particles, which are randomly initialized in the search space. These particles are referred to as swarm. Each particle of the swarm represents a potential solution of the optimization problem. The particles fly through the search space and their positions are updated based on the best positions of individual particles and the best of the swarm in each iteration. The objective function is measured for each particle at each grid point and the fitness values of particles are obtained to determine the best position in the search space (Clerc 2010).

Koay and Srinivasan (2003) introduced a particle swarm optimization-based method for solving a multi-objective generator maintenance scheduling problem with many constraints. They showed that the particle swarm optimization-based approach is effective in obtaining feasible schedules in a reasonable time (Koay and Srinivasan 2003).

Balci and Valenzuela (2004) described a procedure that uses PSO combined with the Lagrangian Relaxation (LR) framework to solve a power-generator scheduling problem known as the unit commitment problem (UCP) (Mika et al. 2008). Ge et al. (2005) developed a PSO-based algorithm for job shop scheduling problems (JSSP) (Ge et al. 2005).

Xia and Wu (2006) proposed a new approximation algorithm for the problem of finding the minimum makespan in the job shop scheduling environment. Their algorithm is based on the principle of particle swarm optimization (Xia and Wu 2006).

Liao et al. (2007) presented a PSO algorithm, extended from discrete PSO, for flow shop scheduling. In the proposed algorithm, the particle and the velocity are redefined, and an efficient approach is developed to move a particle to the new sequence. To verify the proposed PSO algorithm, comparisons with a continuous PSO algorithm and two genetic algorithms are made (Liao et al. 2007).

Sha and Hsu (2008) presented a particle swarm optimization for the open shop scheduling problem. Compared with the original PSO, they modified the particle position representation using priorities, and the particle movement using an insert operator. They also implemented a modified parameterized active schedule generation algorithm (mP-ASG) to decode a particle position into a schedule (Sha and Hsu 2008).

Lin et al. (2010) presented a new hybrid swarm intelligence algorithm consists of particle swarm optimization, simulated annealing technique, and multi-type individual enhancement scheme to solve the job shop scheduling problem. Sha and Lin (2010) constructed a PSO for an elaborate multi-objective job shop scheduling problem. The original PSO was used to solve continuous optimization problems. Due to the discrete solution spaces of scheduling optimization problems, the authors modified the particle position representation, particle movement, and particle velocity in this study (Sha and Lin 2010).

Shiau (2011) proposed an SLS algorithm that is based on the principles of particle swarm optimization for course scheduling problem. In their paper, the algorithm includes some features: designing an 'absolute position value' representation for the particle; allowing instructors that they are willing to lecture based on flexible preferences, such as their preferred days and time periods, the maximum number of teaching-free time periods and the lecturing format (consecutive time periods or separated into different time periods); and employing a repair process for all infeasible timetables. Furthermore, in the original PSO algorithm, particles search solutions in a continuous solution space. Since the solution space of the course scheduling problem is discrete, a local search mechanism is incorporated into the proposed PSO in order to explore a better solution improvement (Shiau 2011).

Liao et al. (2012) presented a particle swarm optimization algorithm for the hybrid flow shops (HFS) scheduling problem with minimum makespan objective. The main contribution of this paper is to develop a new approach hybridizing PSO with bottleneck heuristic to fully exploit the bottleneck stage, and with simulated annealing to help escape from local optima (Liao et al. 2012).

Marimuthu and Naveen Sait (2013) considered n-job, m-machine lot streaming problem in a flow shop with equal size sub lots where the objective is to minimize the makespan and total flow time.

Koulinas et al. (2014) proposed a particle swarm optimization based hyper-heuristic algorithm for solving the resource constrained project scheduling problem (RCPSP).

Nouiri et al. (2015) applied PSO algorithm to solve flexible job shop scheduling problem aiming to minimize the maximum completion time criterion.

AitZai et al. (2016) proposed different resolution methods for no-wait job shop scheduling problem. The first is an exact method based on the branch-and-bound algorithm, in which they defined a new technique of branching. The second is a particular swarm optimization algorithm, extended from the discrete version of PSO (AitZai et al. 2016). Table 10 summarizes the researches have been done in scheduling with particle swarm optimization (PSO).

5.3.1 Strengths and weaknesses of particle swarm optimization

In this subsection, a summary of the strengths and weaknesses of particle swarm optimization is presented (Glover and Kochenberger 2006; Zhan and Huo 2012).

Strengths of particle swarm optimization

- Its simplicity and ease of use.
- It has a high convergence rate.
- PSO is an efficient global optimizer for continuous variable problems.
- Easily implemented, with very little parameters to fine-tune.
- PSO is able to accommodate constraints by using a penalty method.
- PSO has an inbuilt ability to adjust to a dynamic environment.
- PSO is effective for locating and tracking optima in both static and dynamic environments.
- The particle swarm optimizer has been found to be fast in solving nonlinear, non-differentiable, multi-modal problems.
- PSO presents a simple mathematical operation with fewer parameters.
- It is inexpensive in terms of both memory and speed requirements.

Table 10 Scheduling with particle swarm optimization (PSO)

Nos.	Authors	Years	Application or method	References
1	Koay and Srinivasan	2003	Generator maintenance scheduling	Koay and Srinivasan (2003)
2	Balci and Valenzuela	2004	Electric power generators scheduling	Balci and Valenzuela (2004)
3	Liu et al.	2005	Hybrid particle swarm optimization for flow shop scheduling	Liu et al. (2005)
4	Ge et al.	2005	Particle swarm optimization-based algorithm job shop scheduling problem	Ge et al. (2005)
5	Zhang et al.	2006	Resource-constrained project scheduling	Zhang et al. (2006)
7	Xia and Wu	2006	Hybrid particle swarm optimization approach for the job shop scheduling problem	Xia and Wu (2006)
8	Liao et al.	2007	Discrete version of particle swarm optimization for flow shop scheduling problems	Liao et al. (2007)
9	Liu et al.	2007	Hybrid particle swarm optimization for no-wait flow shop scheduling	Liu et al. (2007)
10	Tseng and Liao	2008	Discrete particle swarm optimization for lot-streaming flow shop scheduling problem	Tseng and Liao (2008)
11	Sha and Hsu	2008	Open shop scheduling problem	Sha and Hsu (2008)
12	Mandal et al.	2008	Short-term hydrothermal scheduling	Mandal et al. (2008)
13	Liu et al.	2008	Hybrid PSO-based algorithm for flow shop scheduling with limited buffers	Liu et al. (2008)
14	Anghinolfi and Paolucci	2009	Single-machine total weighted tardiness scheduling problem	Anghinolfi and Paolucci (2009)
15	Kuo et al.	2009	Flow shop scheduling algorithm based on a hybrid particle swarm optimization model	Kuo et al. (2009)
16	Hota et al.	2009	Short-term optimal hydrothermal scheduling	Hota et al. (2009)
17	Lin et al.	2010	Job shop scheduling	Lin et al. (2010)
18	Sha and Lin	2010	Multi-objective PSO for job shop scheduling problems	Sha and Lin (2010)

Table 10 continued

Nos.	Authors	Years	Application or method	References
19	Mathiyalagan et al.	2010	Grid scheduling	Mathiyalagan et al. (2010)
20	Chen	2011	Resource-constrained project scheduling problem	Chen (2011)
21	Shiau	2011	University course scheduling problem	Shiau (2011)
22	Wang et al.	2012	Self-adaptive PSO technique for short-term hydrothermal scheduling	Wang et al. (2012)
23	Liao et al.	2012	Hybrid flow shop scheduling problem	Liao et al. (2012)
24	Mandal and Chakraborty	2012	Daily combined economic emission scheduling of hydrothermal systems	Mandal and Chakraborty (2012)
25	Torabi et al.	2013	Parallel machines scheduling problem	Torabi et al. (2013)
26	Marimuthu and Sait	2013	M-machine flow shops	Marimuthu and Naveen Sait (2013)
27	Marinakis and Marinaki	2013	Permutation flow shop scheduling problem	Marinakis and Marinaki (2013)
28	Koulinas et al.	2014	Classic resource constrained project scheduling problem	Koulinas et al. (2014)
29	Chen et al.	2014	Permutation flow shop scheduling problem	Chen et al. (2014)
30	Tsai et al.	2014	Hybrid sliding level Taguchi-based particle swarm optimization	Tsai et al. (2014)
31	Nouiri et al.	2015	Flexible job shop scheduling problem	Nouiri et al. (2015)
32	Wang et al.	2015	No-wait hybrid flow shop	Wang et al. (2015)
33	Karimi-Nasab et al.	2015	Joint lot sizing and job shop scheduling	Karimi-Nasab et al. (2015)
34	AitZai et al.	2016	No-wait job shop scheduling	AitZai et al. (2016)
35	Singh and Mahapatra	2016	Quantum behaved particle swarm optimization for flexible job shop scheduling	Singh and Mahapatra (2016)
36	Jia et al.	2016	Permutation flow shop scheduling problem	Jia et al. (2016)

Weaknesses of particle swarm optimization

- Weak local search ability: It is easy to fall into local optimum in high-dimensional space.
- When used for multi-objective optimization, are mainly related to the apparent difficulties to control diversity.

5.4 Ant colony optimization

Ant colony optimization (ACO) was first proposed by Dorigo et al. (1982). Ant colony optimization is an SLS method for solving hard combinatorial optimization problems. It is inspired by the foraging behavior of ants through their deposit of pheromone where they are able to identify the shortest path to transport their food. Notwithstanding, it is a stochastic and multi-directional search algorithm, it does not guarantee the discovery of an optimal solution. The algorithm is developed based on a parameterized probabilistic model known as the pheromone model with various pheromone values. A pheromone value is associated to each pheromone trail and is updated during every runtime in order to obtain a bias towards high quality solutions (Teoh et al. 2015).

Yu et al. (1998) presented a new cooperative agents approach, the ant colony search algorithm (ACSA), for solving a short-term generation scheduling problem of a thermal power system. One of the main goals of the authors is to investigate the applicability of an alternative intelligent search method in power system optimization (Yu et al. 1998).

Van Der Zwaan and Marques (1999) outlined the ant colony optimization algorithm's implementation and performance when applied to job shop scheduling. The algorithm parameter settings seem to play a crucial role in its efficiency and determine the quality of solutions. In their work, they presented some statistical analysis for parameter tuning and they compared the quality of obtained solutions for well-known benchmark problems in job shop scheduling (Van Der Zwaan and Marques 1999).

Jayaraman et al. (2000) presented a new co-operative search approach, the ant colony optimization paradigm, for the optimal design of batch chemical processes and illustrates it by solving (1) the combinatorial optimization problem of multiproduct batch scheduling and (2) the continuous function optimization problem for the design of multiproduct batch plant with single product campaigns and horizon constraints (Jayaraman et al. 2000).

Huang (2001) proposed an ant colony system (ACS) based optimization approach for the enhancement of hydroelectric generation scheduling.

Blum (2005) hybridized the solution construction mechanism of ACO with beam search, which is a well-known tree search method. Blum called this approach Beam-ACO. In this paper, the usefulness of Beam-ACO is demonstrated by its application to open shop scheduling (OSS) (Blum 2005).

Huang and Liao (2008) presented a hybrid algorithm combining ant colony optimization algorithm with the tabu search algorithm for the classical job shop scheduling problem. Instead of using the conventional construction approach to construct feasible schedules, the proposed ant colony optimization algorithm employs a decomposition method inspired by the shifting bottleneck procedure and a mechanism of occasional re-optimizations of partial schedules. Besides, a tabu search algorithm is embedded to improve the solution quality (Huang and Liao 2008).

Xing et al. (2010) proposed a Knowledge-Based Ant Colony Optimization (KBACO) algorithm for the flexible job shop scheduling problem. In this paper, KBACO algorithm provides an effective integration between Ant Colony Optimization (ACO) model and knowledge model.

Wu et al. (2012) proposed the demand forecasting model based on BP neural network to address the master production scheduling optimization problem. Moreover, they designed a simulation example and several error indexes to evaluate and analyze the performance of the proposed method (Wu et al. 2012).

Chen and Zhang (2013) developed a novel approach with an event-based scheduler (EBS) and an ant colony optimization algorithm to develop a flexible and effective model for software project planning.

By observing similarities between operating room surgery scheduling and a multi-resource constraint flexible job shop scheduling problem in manufacturing, Xiang et al. (2015) proposed an ACO approach to efficiently solve such surgery scheduling problems based on the knowledge gained in FJSSP (Xiang et al. 2015).

Liu et al. (2016) proposed an optimization algorithm base on ant colony optimization for integrated process planning and scheduling, which can handle the dynamic emergency situation. Firstly, they proposed the representation mechanisms of candidate operation and the scheduling scheme construction mechanism. Then, they presented the process constraints and time cost functions; based on this, they constructed the mathematical model. The ACO algorithm has been developed to solve the proposed mathematical model of integrated process planning and scheduling (Liu et al. 2016). Table 11 summarizes the researches have been done in scheduling with ant colony optimization (ACO).

5.4.1 Strengths and weaknesses of ant colony optimization

In this subsection, a summary of the strengths and weaknesses of ant colony optimization is presented (Glover and Kochenberger 2006; Dorigo and Blum 2005).

Strengths of ant colony optimization

- Distributed computation avoids premature convergence.
- It does not require an explicit mechanism to keep diversity since diversity is really produced in an emergent fashion by the action selection mechanism adopted (this mechanism performs a random action with a low probability).
- Inherent parallelism.
- Another interesting aspect is that the changes proposed by the negotiation mechanism of the algorithm are done in decision variable space rather than in objective function space.
- Positive feedback leads to rapid discovery of good solutions.
- Can be used in dynamic applications.
- Efficient solving traveling salesman problem and other discrete problems.
- Weaknesses of ant colony optimization.
- Theoretical analysis is difficult.
- Sequences of random decisions. In fact, they are not independent.
- Probability distribution changes by iteration.
- Convergence is guaranteed, but time to convergence is uncertain.
- Not effective in solving the continuous problems.

5.5 Evolutionary approaches

In this section, first, we define the Evolutionary Approaches and then survey the researches that have been done in this area. Evolutionary Computation is an abstraction from the theory of biological evolution that is used to create optimization procedures or methodologies, usually implemented on computers that are used to solve problems. Evolutionary approaches have been shown in Fig. 6.

Table 11 Scheduling with ant colony optimization (ACO)

Nos.	Authors	Years	Application or method	References
1	Yu et al.	1998	Short-term generation scheduling problem of thermal units	Yu et al. (1998)
2	Van Der Zwaan and Marques	1999	Ant colony optimization for job shop scheduling	Van Der Zwaan and Marques (1999)
3	Jayaraman et al.	2000	Batch plants scheduling	Jayaraman et al. (2000)
4	Huang	2001	Hydroelectric generation scheduling	Huang (2001)
5	Teich et al.	2001	Job shop scheduling problem	Teich et al. (2001)
6	T'kindt et al.	2002	Two-machine bi-criteria flow shop scheduling problem	T'kindt et al. (2002)
7	Ying and Liao	2003	Ant colony system approach for scheduling problems	Ying and Liao (2003)
8	Rajendran and Ziegler	2004	Permutation flow shop scheduling	Rajendran and Ziegler (2004)
9	Blum and Sampels	2004	ACO for shop scheduling problems	Blum and Sampels (2004)
10	Blum	2005	Hybridizing ant colony optimization with beam search for open shop scheduling	Blum (2005)
11	Dowsland and Thompson	2005	Examination scheduling problem	Dowsland and Thompson (2005)
12	Ying and Lin	2006	Multiprocessor task scheduling in multistage hybrid flow shops	Ying and Lin (2006)
13	Raghavan and Venkataramana	2006	Scheduling parallel batch processors with incompatible job families	Raghavan and Venkataramana (2006)
14	Liao and Juan	2007	Single-machine tardiness scheduling with sequence-dependent setups	Liao and Juan (2007)
15	Gutjahr and Rauner	2007	Dynamic regional nurse-scheduling problem	Gutjahr and Rauner (2007)
16	Huang and Liao	2008	Ant colony optimization combined with tabu search	Huang and Liao (2008)
17	Seçkiner and Kurt	2008	Job rotation scheduling	Seçkiner and Kurt (2008)
18	Marimuthu et al.	2009	Scheduling m-machine flow shops with lot streaming	Marimuthu et al. (2009)
19	Eswaramurthy and Tamilarasi	2009	Hybridizing tabu search with ant colony optimization	Eswaramurthy and Tamilarasi (2009)
20	Xing et al.	2010	Knowledge-based ant colony optimization	Xing et al. (2010)
21	Berrichi et al.	2010	Bi-objective ant colony optimization approach	Berrichi et al. (2010)

Table 11 continued

Nos.	Authors	Years	Application or method	References
22	Neto and Godinho Filho	2011	Permutational flow shop scheduling with outsourcing allowed	Neto and Godinho Filho (2011)
23	Deng and Lin	2011	Airline crew scheduling problem	Deng and Lin (2011)
24	Guo et al.	2012	Scheduling semiconductor wafer fabrication system	Guo et al. (2012)
25	Srikanth et al.	2012	Tasks scheduling	Srikanth et al. (2012)
26	Wu et al.	2012	Master production scheduling optimization	Wu et al. (2012)
27	Chen and Zhang	2013	Software project scheduling and staffing with an event-based scheduler	Chen and Zhang (2013)
28	Xiao et al.	2013	Software project scheduling problems	Xiao et al. (2013)
29	Zhang et al.	2014	Multi-satellite control resource scheduling	Zhang et al. (2014)
30	Tiwari and Vidyarthi	2014	Scheduling on computational grid	Tiwari and and (2014)
31	Cheng et al.	2015	Integrated scheduling of production and distribution	Cheng et al. (2015)
32	Neto et al.	2015	Parallel machine scheduling problem with outsourcing allowed	Neto et al. (2015)
33	Xiang et al.	2015	Operating room surgery scheduling problem	Xiang et al. (2015)
34	Liu et al.	2016	Integrated process planning and scheduling	Liu et al. (2016)
35	Wang et al.	2016	Scheduling overlapping architectural design activities	Wang et al. (2016)
36	Elmi and Topaloglu	2016	Multi-degree cyclic flow shop robotic cell scheduling problem	Elmi and Topaloglu (2016)

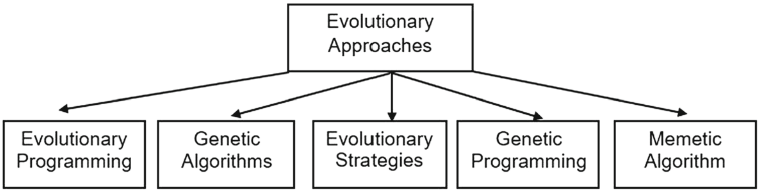

Fig. 6 Evolutionary approaches

5.5.1 Genetic algorithms

There is another class of new optimization routines known collectively as Genetic Algorithms. These attempt to simulate the phenomenon of natural evolution first observed by Darwin (1859) and elaborated by Dawkins (1986). In natural evolution, each species searches for beneficial adaptations in an ever-changing environment. As species evolve these new attributes are encoded in the chromosomes of individual members. This information does change by random mutation, but the real driving force behind evolutionary development is the combination and exchange of chromosomal material during breeding. Although sporadic attempts to incorporate these principles in optimization routines have been made since the early 1960s, GAs were first established on a sound theoretical basis by Holland (1975). The two key axioms underlying this innovative work were that complicated non-biological structures could be described by simple bit strings and that these structures could be improved by the application of simple transformations to these strings. GAs differ from traditional optimization algorithms in four important respects:

- They work using an encoding of the control variables, rather than the variables themselves.
- They search from one population of solutions to another, rather than from individual to individual.
- They use only objective function information, not derivatives.
- They use probabilistic, not deterministic, transition rules.

Lee et al. (1988) considered the problem of scheduling a set of n partially ordered tasks on m identical processors in order to minimize the makespan, where there is a communication delay between any pair of distinct processors. They proposed a heuristic algorithm to solve the problem (Lee et al. 1988).

The task of generating inputs to the GA process for the Job Shop Scheduling problem was presented by Biegel and Davern (1990). This technique employed an extension to the Group Technology (GT) method for generating manufacturing process plans (Biegel and Davern 1990).

A genetic recombination operator for the traveling salesman problem which preserves adjacency was developed by Starkweather et al. (1992).

Gupta et al. (1993) proposed a heuristic procedure based on genetic algorithms with the potential to address more generalized objective function such as weighted flow time variance for an n-job, single machine scheduling problem with an objective to minimize the flow time variance.

Della Croce et al. (1995) introduced a genetic algorithm whose peculiarities are the introduction of an encoding based on preference rules and an updating step which speeds up the evolutionary process. This method improved on the results gained previously with genetic algorithms and had shown itself to be competitive with other heuristics (Della Croce et al. 1995).

A heuristic approach based on a genetic algorithm was developed by Wang et al. (1997) to do matching and scheduling in heterogeneous computing environments. It is assumed that the matcher/scheduler was in control of a dedicated HC suite of machines (Wang et al. 1997).

Hartmann (1998) considered the resource-constrained project scheduling problem (RCPSP) with makespan minimization as objective. They proposed a permutation based genetic approach to solve this problem (Hartmann 1998).

Liaw (2000) presented a hybrid genetic algorithm (HGA) to the open shop scheduling problem. The hybrid algorithm incorporated a local improvement procedure based on tabu search (TS) into a basic genetic algorithm (GA). The incorporation of the local improvement procedure enabled the algorithm to perform genetic search over the subspace of local optima (Liaw 2000).

Hartmann (2001) proposed a self-adapting genetic algorithm to solve the resource-constrained project scheduling problem. The heuristic employed the well-known activity list representation and considers two different decoding procedures. An additional gene in the representation determined which of the two decoding procedures was actually used to compute a schedule for an individual. This allowed the genetic algorithm to adapt itself to the problem instance actually solved (Hartmann 2001).

A hybrid genetic algorithm (HGA) is proposed for permutation flow shop scheduling with limited buffers was presented by Wang et al. (2006). In the HGA, not only multiple genetic operators based on evolutionary mechanism were used simultaneously in hybrid sense, but also a neighborhood structure based on graph model was employed to enhance the local search so that the exploration and exploitation abilities could be well balanced. Moreover, a decision probability was used to control the utilization of genetic mutation operation (Wang et al. 2006).

Gao et al. (2007) addressed the flexible job shop scheduling problem with three objectives: min makespan, min maximal machine workload, and min total workload. The authors developed a genetic algorithm hybridized with an innovative local search procedure for this problem. The genetic algorithm used two representation methods to depict solution candidates of the FJSP problem. Advanced crossover and mutation operators were proposed to adapt to the special chromosome structures and the characteristics of the problem (Gao et al. 2007).

A genetic algorithm for the resource constrained multi-project scheduling problem was introduced by Gonçalves et al. (2008). The chromosome representation of the problem was based on random keys. The schedules were constructed using a heuristic that built parameterized active schedules based on priorities, delay times, and release dates defined by the genetic algorithm (Gonçalves et al. 2008).

Mendes et al. (2009) presented a genetic algorithm for the resource constrained project scheduling problem (RCPSP). The chromosome representation of the problem was based on random keys. The schedule was constructed using a heuristic priority rule in which the priorities of the activities were defined by the genetic algorithm (Mendes et al. 2009).

Van Peteghem and Vanhoucke (2010) proposed a genetic algorithm for the multi-mode resource-constrained project scheduling problem (MRCPSP), in which multiple execution modes were available for each of the activities of the project. They also introduced the preemptive extension of the problem which allows activity splitting (P-MRCPSP). To solve the problem, the authors applied a bi-population genetic algorithm, which makes use of two separate populations and extends the serial schedule generation scheme by introducing a mode improvement procedure (Van Peteghem and Vanhoucke 2010).

A genetic algorithm was presented by Vallada and Ruiz (2011) for the unrelated parallel machine scheduling problem in which machine and job sequence dependent setup times were considered. The proposed genetic algorithm includes a fast local search and a local search enhanced crossover operator (Vallada and Ruiz 2011).

Based on genetic algorithm and grouping genetic algorithm, Chen et al. (2012) developed a scheduling algorithm for job shop scheduling problem with parallel machines and reentrant process. This algorithm consisted of two major modules: machine selection module (MSM) and operation scheduling module (OSM). MSM helped an operation to selected one of the parallel machines to process it. OSM was then used to arrange the sequences of all operations assigned to each machine (Chen et al. 2012).

A task scheduling scheme on heterogeneous computing systems using a multiple priority queues genetic algorithm (MPQGA) was proposed by Xu et al. (2014). The basic idea of this approach was to exploit the advantages of both evolutionary-based and heuristic-based algorithms while avoiding their drawbacks. The proposed algorithm incorporated a genetic algorithm approach to assign a priority to each subtask while using a heuristic-based earliest finish time (EFT) approach to search for a solution for the task-to-processor mapping (Xu et al. 2014).

The mathematical programming model for the steel-making continuous casting scheduling problem was established based on unit-specific event-point continuous-time representation by Li et al. (2015a). Then, an improved self-adaptive genetic algorithm (SAGA) was proposed to optimize the sequence among casts with the objective of reducing the total idle times on all machines and minimizing the makespan. In SAGA, the probabilities of crossover and mutation rate were rectified exquisitely and automatically so as to avoid being trapped in local optima and neighborhood-based mutation operation was adopted to improve the diversity (Li et al. 2015b). Table 12 summarizes the researches have been done in scheduling with Genetic Algorithm (GA).

5.5.2 Other evolutionary approaches

Finding feasible schedules for tasks running in hard, real-time distributed computing systems is generally NP-hard. Greenwood et al. (1994) presented a solution to the multiprocessor scheduling problem based on Evolutionary Strategies. Results of this research indicated that the evolutionary strategies can find feasible schedules in very short periods of time (Greenwood et al. 1994).

Gupta and Greenwood (1996) described a heuristic embedding technique based on evolutionary strategies. The technique had been extensively investigated using task graphs which were trees, forests, and butterflies (Gupta and Greenwood 1996).

Lai et al. (1998) proposed a multi-time-interval scheduling for the daily operation of a two-cogeneration system connected with auxiliary devices. The efficiency of a cogeneration system depended on the production of thermal and electrical energy which was modeled with a quadratic equation obtained by the least-squares method. Evolutionary programming (EP) was used to establish operation scheduling for the cogeneration system (Lai et al. 1998).

Seredyński et al. (1999) developed a parallel and distributed scheduling algorithms for multiprocessor systems. A program graph was interpreted as a multi-agent system. A game-theoretic model of interaction between agents was applied. Competitive co-evolutionary genetic algorithm, termed loosely coupled genetic algorithm, was used to implement the multi-agent system (Seredyński et al. 1999).

The set covering problem is a paradigmatic NP-hard combinatorial optimization problem which is used as a model in crew scheduling in airlines and mass-transit companies. Marchiori and Steenbeek (2000) concerned with the approximated solution of large scale set covering problems arising from crew scheduling in airline companies. They proposed an adaptive heuristic-based evolutionary algorithm whose main ingredient was a mechanism for selecting a small core sub-problem which was dynamically updated during the execution. This mechanism allowed the algorithm to find covers of good quality in rather short time (Marchiori and Steenbeek 2000).

A memetic algorithm (MA) for the total tardiness single machine scheduling (SMS) problem with due dates and sequence-dependent setup times was proposed by França et al. (2001). Concerning the local improvement procedure, several neighborhood reduction schemes were

Table 12 Scheduling with genetic algorithm (GA)

Nos.	Authors	Years	Application or method	References
1	Lee et al.	1988	Multiprocessor scheduling	Lee et al. (1988)
2	Biegel et al.	1990	Generating inputs to the GA	Biegel and Davern (1990)
3	Starkweather et al.	1992	Sequence scheduling	Starkweather et al. (1992)
4	Gupta et al.	1993	Single machine scheduling problem	Gupta et al. (1993)
5	Della Croce et al.	1995	Encoding based genetic algorithm	Della Croce et al. (1995)
6	Wang et al.	1997	Heterogeneous computing environments	Wang et al. (1997)
7	Hartmann	1998	Permutation based genetic algorithm	Hartmann (1998)
8	Liaw	2000	Hybrid of tabu search and genetic algorithm	Liaw (2000)
9	Cai and Li	2000	Staff scheduling	Cai and Li (2000)
10	Hartmann	2001	Resource-constrained project scheduling problem	Hartmann (2001)
11	Pongcharoen et al.	2002	Determining optimum genetic algorithm parameters	Pongcharoen et al. (2002)
12	Cochran et al.	2003	Multi-population genetic algorithm	Cochran et al. (2003)
13	Iyer and Saxena	2004	Permutation flow shop scheduling	Iyer and Saxena (2004)
14	Chan et al.	2005	Adaptive genetic algorithm with dominated genes	Chan et al. (2005)
15	Wang et al.	2006	Permutation flow shop scheduling with limited buffers.	Wang et al. (2006)
16	Gao et al.	2007	Genetic algorithm hybridized with an innovative local search procedure	Gao et al. (2007)
17	Jia et al.	2007	Integration of genetic algorithm and Gantt chart	Jia et al. (2007)
18	Gonçalves et al.	2008	Resource constrained multi-project scheduling problem	Gonçalves et al. (2008)
19	Asokan et al.	2008	Adaptive genetic algorithm	Asokan et al. (2008)
20	Mendes et al.	2009	Random key based genetic algorithm	Mendes et al. (2009)
21	Gu et al.	2009	Parallel quantum genetic algorithm	Gu et al. (2009)
22	Van Peteghem et al.	2010	Bi-population genetic algorithm	Van Peteghem and Vanhoucke (2010)
23	Vallada et al.	2011	Unrelated parallel machine scheduling problem	Vallada and Ruiz (2011)

Table 12 continued

Nos.	Authors	Years	Application or method	References
24	Wang et al.	2011	Adaptive genetic algorithm	Wang and Tang (2011)
25	Chen et al.	2012	Grouping Genetic Algorithm	Chen et al. (2012)
26	Chung et al.	2012	Quay crane schedule problems	Chung and Choy (2012)
27	Zamani	2013	Competitive magnet-based genetic algorithm	Zamani (2013)
28	Ventura and Yoon	2013	Lot-streaming flow shop scheduling	Ventura and Yoon (2013)
29	Chang et al.	2013	Block mining and re-combination enhanced genetic algorithm	Chang et al. (2013)
30	Xu et al.	2014	Multiple priority queues genetic algorithm	Xu et al. (2014)
31	Chang et al.	2014	Greedy-search-based multi-objective genetic algorithm	Chang et al. (2014)
32	Gonçalves and Resende	2014	Biased random-key genetic algorithm	Gonçalves and Resende (2014)
33	Zhang and Wong	2015	Object-coding genetic algorithm	Zhang and Wong (2015)
34	Trivedi et al.	2015	Hybridizing genetic algorithm with differential evolution	Trivedi et al. (2015)
35	Li et al.	2015	Heuristic-search genetic algorithm	Li et al. (2015)
36	Damm et al.	2016	Biased random key genetic algorithm	Damm et al. (2016)
37	Jorapur et al.	2016	Promising Initial Population Based Genetic Algorithm	Jorapur et al. (2016)
38	Zhang and Chiong	2016	Multi-objective genetic algorithm with enhanced local search	Zhang and Chiong (2016)

developed and proved to be effective when compared to the complete neighborhood (França et al. 2001).

Multi-objective Evolutionary Algorithms (MOEAs) were presented by Barán et al. (2005) to solve an optimal pump-scheduling problem with four objectives to be minimized: electric energy cost, maintenance cost, maximum power peak, and level variation in a reservoir. Six different MOEAs were implemented and compared. In order to consider hydraulic and technical constraints, a heuristic algorithm was developed and combined with each implemented MOEA (Barán et al. 2005).

A memetic algorithm based on differential evolution (DE), named MODEMA, was proposed by Qian et al. (2008) for multi-objective job shop scheduling problems. To balance the exploration and exploitation abilities, both DE-based global search and an adaptive local search were designed and applied simultaneously in the proposed MODEMA (Qian et al. 2008).

Liang et al. (2009) addressed the problem of determining the berthing position and time of each ship as well as the number of quay cranes assigned to each ship. The objective of the problem was to minimize the sum of the handling time, waiting time and the delay time for every ship. They introduced a formulation for the simultaneous berth and quay crane scheduling problem. This paper combined genetic algorithm with heuristic to find an approximate solution for the problem (Liang et al. 2009).

Frutos et al. (2010) introduced a memetic algorithm, based on a non-dominated sorting genetic algorithm acting on two chromosomes, to solve the flexible job shop Scheduling Problem. The algorithm added, to the genetic stage, a local search procedure [Simulated Annealing (Frutos et al. 2010)].

A parallel job scheduling algorithm for a grid environment was presented by Switalski and Seredynski (2011). The model implied two-stage scheduling. At the first stage, algorithm allocated jobs to the suitable machines, where at the second stage jobs were independently scheduled on each machine. Allocation of jobs on the first stage of the algorithm was performed with use of a relatively new evolutionary algorithm called Generalized Extremal Optimization (GEO). GEO was inspired by a simple co-evolutionary model known as Bak-Sneppen model. Scheduling on the second stage was performed by some proposed heuristic (Switalski and Seredynski 2011).

Nguyen et al. (2012) proposed two genetic programming (GP) methods to evolve general due date assignment models (DDAMs) for job shop environments.

A memetic algorithm was proposed by Soukour et al. (2013) to solve job shop scheduling problems. The proposed method was a genetic-algorithm-based approach combined with a local search heuristic. Moreover, in this article, a new fitness function was introduced for JSSPs. The new fitness function called priority-based fitness function was defined in three priority levels to improve the selection procedure (Soukour et al. 2013).

Xu et al. (2010a) presented a systematic comparison of hybrid evolutionary algorithms (HEAs), which independently used six combinations of three crossover operators and two population updating strategies, for solving the single machine scheduling problem with sequence-dependent setup times. Experiments showed the competitive performance of the combination of the linear order crossover operator and the similarity-and-quality based population updating strategy (Xu et al. 2010b).

Park et al. (2015) considered static JSS problems with makespan minimization. Hyper-heuristics (HHs) had been proposed as an approach to automating the design of heuristics. The evolved heuristics had been priority based dispatching rules (DRs). To improve the robustness of evolved heuristics generated by HHs, this paper proposed a new approach where an ensemble of rules evolved using Genetic Programming (GP) and cooperative coevolution, denoted as Ensemble Genetic Programming for job shop scheduling (Park et al. 2015).

A competitive memetic algorithm (CMA) was proposed by Deng et al. (2016) for the distributed two-stage assembly flow shop scheduling problem (DTSAFSP) with makespan minimization criterion. A simple encoding scheme was proposed to represent the factory assignment and the job processing sequence; and a ring-based neighborhood structure was designed for competition and information sharing. Moreover, some knowledge-based local search operators were developed to enhance the exploitation ability (Deng et al. 2016). Table 13 summarizes the researches have been done in scheduling with the other evolutionary approaches in Scheduling.

Table 13 The other evolutionary approaches in scheduling

Nos.	Authors	Years	Application	References	Nos.
1	Greenwood et al.	1994	ES	Multiprocessor scheduling problem	Greenwood et al. (1994)
2	Gorrini and Dorigo	1995	EP	Robotic operations	Gorrini and Dorigo (1995)
3	Gupta et al.	1996	ES	Fine-grained task scheduling	Gupta and Greenwood (1996)
4	Dasgupta	1997	EP	Thermal power generation	Cheng and Gen (1997)
5	Lai et al.	1998	EP	Multi-time-interval scheduling	Lai et al. (1998)
6	Seredyński et al.	1999	GP	Multiprocessor systems	Seredyński et al. (1999)
7	Marchiori et al.	2000	EP	Airline crew scheduling.	Marchiori and Steenbeek (2000)
8	Miyashita	2000	GP	Job shop scheduling problem	Miyashita (2000)
9	França et al.	2001	MA	Single machine scheduling problem	França et al. (2001)
10	Yeh	2002	MA	Flow shop scheduling problem	Yeh (2002)
11	Esquivel et al.	2002	EP	Multi-objective optimization in the job shop scheduling	Esquivel et al. (2002)
12	Ishibuchi et al.	2003	MA	Multi-objective permutation flow shop scheduling	Ishibuchi et al. (2003)
13	Sinha et al.	2003	EP	Short-term hydrothermal scheduling	Sinha et al. (2003)
14	Lee and Asllani	2004	GP	Dual criteria scheduling	Lee and Asllani (2004)
15	Barán et al.	2005	ES	Multi-objective pump scheduling	Barán et al. (2005)
16	Cotta et al.	2006	EP	Social golfer problem	Cotta et al. (2006)
17	Lei and Wu	2006	EP	Job shop scheduling problem.	Lei and Wu (2006)
18	Cotta and Fernández	2007	MA	Scheduling and timetabling.	Cotta and Fernández (2007)
19	Ripon et al.	2007	EP	Multi-objective job shop scheduling problem	Ripon et al. (2007)
20	Qian et al.	2008	MA	Multi-objective job shop scheduling problem	Qian et al. (2008)
21	Marimuthu et al.	2008	EP	M-machine flow shop with lot streaming	Marimuthu et al. (2008)

Table 13 continued

Nos.	Authors	Years	Application	References	Nos.
22	Liang et al.	2009	EP	Quay crane dynamic scheduling	Liang et al. (2009)
23	Martin	2009	GP	Multi-family flow shop scheduling problem	Martin (2009)
24	Frutos et al.	2010	MA	Flexible job shop scheduling problem	Frutos et al. (2010)
25	Elloumi and Fortemps	2010	EP	Multi-mode resource-constrained project scheduling problem	Elloumi and Fortemps (2010)
26	Switalski et al.	2011	ES	Parallel job model in grid environment	Switalski and Seredynski (2011)
27	Chiang and Lin	2011	MA	Flexible job shop scheduling	Chiang and Lin (2011)
28	Nguyen et al.	2012	GP	Job shop scheduling problems	Nguyen et al. (2012)
29	Sutton and Neumann	2012	EP	Makespan Scheduling on two machines	Sutton and Neumann (2012)
30	Soukour et al.	2013	MA	Staff scheduling problem in airport security service	Soukour et al. (2013)
31	Chiang and Lin	2013	ES	Multi-objective flexible job shop scheduling problem	Chiang and Lin (2013)
32	Nguyen et al.	2013	GP	Dynamic multi-objective job shop scheduling	Nguyen et al. (2013)
33	Xu et al.	2014	EP	Single machine scheduling problem	Xu et al. (2014)
34	Xu et al.	2014	MA	Re-entrant permutation flow shop scheduling problem	Xu et al. (2014)
35	Park et al.	2015	GP	Static job shop scheduling problems	Park et al. (2015)
36	Hsu et al.	2015	EP	Permutation flow shop scheduling problem	Hsu et al. (2015)
37	Lin et al.	2015	MA	Nurse preference scheduling problems	Lin et al. (2015)
38	Wang et al.	2016	EP	Dynamic multi-objective machine scheduling problem	Wang et al. (2016)
39	Jin et al.	2016	MA	Process planning and scheduling	Jin et al. (2016)
40	Deng et al.	2016	MA	Distributed shop scheduling	Deng et al. (2016)
41	Park et al.	2016	GP	Dynamic job shop scheduling	Park et al. (2016)

In this table EP means Evolutionary Programming, ES means Evolutionary Strategies, GP is equal to Genetic Programming and MA means Memetic Algorithm

5.5.3 Strengths and weaknesses of evolutionary approaches

In this subsection, a summary of the strengths and weaknesses of genetic algorithms as an important part of evolutionary approaches is presented (Glover and Kochenberger 2006; Sivanandam and Deepa 2008).

Strengths of genetic algorithms

- Exploring a search space without completely losing partial solutions that have already been found.
- Efficient to solve continuous problems.
- The random mutation guarantees to some extent that we see a wide range of solutions.
- Suitable for parallel processing.
- Traveling in a search space with more individuals so they are less likely to get stuck in local extreme like some other methods.
- Easy to implement.
- Make no assumptions about the problem space.

Weaknesses of genetic algorithms

- Might not find any satisfactory partial solution.
- Tuning can be a challenge.
- High computational cost.
- Premature convergence.
- Difficult to encode a problem in the form of a chromosome.

6 Scheduling with constraint programming

CP is an approach for formulating and solving discrete variable constraint satisfaction or constrained optimization problems that systematically employs deductive reasoning to reduce the search space and allows for a wide variety of constraints. CP extends the power of logic programming through application of more powerful search strategies and the capability to control their design using problem-specific knowledge (Kanet et al. 2004).

CP involves the use of a mathematical/logical modeling language for encoding the formulation, and allows the user to apply a wide range of search strategies, including customized search techniques for finding solutions. CP is very flexible in terms of formulation power and solution approach, but requires skill in declarative-style logic programming and in developing good search strategies (Kanet et al. 2004).

Constraint programming, a relatively new technique for solving optimization problems, has its roots in artificial intelligence and computer science. Lustig and Puget trace the history of CP from initial work on constraint satisfaction problems in the 1970s (2001). Research on arc-consistency techniques formed the foundation of CP literature and the development of computer languages specifically for combinatorial problems followed. In the 1980s, this led to the addition of constraint satisfaction algorithms to the Prolog language and then the addition of constraint programming features to general purpose programming languages in the 1990s. Since its inception, constraint programming has seen success in solving optimization problems of a combinatorial nature, most notably in sequencing and scheduling applications (Heist 2003).

The creation of the optimization programming language (OPL) by Van Hentenryck was a major step toward integrating constraint programming with traditional mathematical programming techniques. Since the late 1990s, the idea of integrating constraint programming and mathematical programming has taken off, resulting in a number of research papers comparing constraint programming with traditional mathematical programming (Van Hentenryck 1999).

Weil et al. (1995) presented the efficiency of constraint programming for solving nurse scheduling problem. The advantages of implementing this method are: (1) it saves much time for the head nurse in the generation of schedules. (2) The proposed system is not a rigid tool for schedule generation, but it is designed to help the decision maker in decisions and negotiations. (3) The proposed system is a flexible tool with respect to individual requests and for overcoming unforeseen absences. (4) It is very easy to manage constraints whether, for example, to define new constraints, activating or deactivating particular constraints, or modifying an already defined constraint (Weil et al. 1995).

Schaerf (1999) tackled the problem of scheduling the matches of a round robin tournament for a sport league. He formally defined the problem, stated its computational complexity, and presented a solution algorithm using a two-step approach. The first step is the creation of a tournament pattern and is based on known graph-theoretic results. The second one is an assignment problem and it is solved using a constraint-based depth-first branch and bound procedure that assigns actual teams to numbers in the pattern (Schaerf 1999).

Harjunkoski et al. (2000) presented two methods to overcome the combinatorial complexity when solving large discrete optimization problems. The basic idea relies on combining mixed integer programming (MIP) and constraint logic programming (CLP) to exploit their complementary strengths. These strategies are illustrated in the area of job-shop scheduling and trim-loss problems. Comparisons of the strategies are presented with direct solutions on MIP and CLP problems (Harjunkoski et al. 2000).

Harjunkoski and Grossmann (2001) proposed a hybrid method for solving multistage scheduling problem. The major challenge in this method lies in generating cuts for assignments that do not exclude feasible solutions, but are strong enough to reduce the search space. The results have shown that order magnitude reductions can be achieved in computation (Harjunkoski and Grossmann 2001). They also presented two strategies to reduce the combinatorial complexity when solving single stage and multistage optimization scheduling problems that involve cost minimization and due dates. These problems can naturally be decomposed into assignment and sequencing subproblems. The proposed strategies rely on either combining mixed-integer programming (MILP) to model the assignment part and constraint programming (CP) for modeling the sequencing part or else combining MILP models for both parts. The subproblems are solved sequentially by adding integer cuts to the first MILP to generate new assignments (Harjunkoski and Grossmann 2002).

Chan and Hao (2002) showed how constraint programming (CP) can be applied in production scheduling for precast plants. They described a constrained precast scheduling model that incorporates the key constraints and objectives considered by production schedulers. A capacity-based backward-scheduling earliest due date rule and a CP approach are developed to solve the model (Chan and Hao 2002). Yun and Gen (2002) considered a preemptive and non-preemptive scheduling model as one of the advanced scheduling problems considered by a constraint programming technique and proposed a new genetic algorithm (GA) considering simultaneously the preemptive and non-preemptive cases of the activities of jobs under single machine job-shop scheduling problems. In the proposed GA, they developed a new method for representing the chromosome of GA. For various comparisons, they also proposed the hybrid GAs with the proposed GA and conventional sequencing rules. These hybrid GAs are applied to several job-shop scheduling problems under a single machine (Yun and Gen 2002).

Kuchcinski and Wolinski (2003) presented global high-level synthesis (HLS) approach which addresses the problem of synthesis of conditional behaviors under resource constraints. In proposed methodology, the conditional behaviors are represented by hierarchical conditional dependency graphs (HCDG) and synthesized using derived constraints programming (CP) models. Their synthesis methods exploit multicycle operations and chaining as well as conditional resource sharing and speculative execution at the same time (Kuchcinski and Wolinski 2003).

Mladenovic et al. (2004) used a constraint programming approach in order to solve the problem of train or trip scheduling on railway network. In this paper, to improve the time performance of available constraint programming tool and to meet the rescheduling requirements, three classes of heuristics working together in seeking the solution have been proposed, denoted as separation heuristics, bound heuristic and search heuristic (Mladenovic et al. 2004).

Sevaux et al. (2005) developed a genetic algorithm and a constraint programming based branch-and-bound algorithm to solve multiprocessor task scheduling problem in hybrid flow-shop environments. Then, they combined these two approaches to benefit from their different aspects (Sevaux et al. 2005). Li et al. (2005) presented a constraint programming approach to optimal steelmaking process scheduling with constraints of processing time, limited waiting time between adjacent stages, serial batching, sequence independent setup time, release/due time, and with the objective of minimizing maximal total waiting time between adjacent charges in the same casts (Li et al. 2005). Quiroga et al. (2005) presented a novel constraint programming formulation that addresses the scheduling problem associated to a class of flexible manufacturing system (FMS). It tackles the problem in a global way by considering the tool allocation, machine assignment, routing and scheduling decisions, altogether in the formulation. Moreover, it is able to take into account a variety of objective functions (Quiroga et al. 2005).

Russell and Urban (2006) considered the problem of scheduling sports competitions over several venues which are not associated with any of the competitors. In this paper, they developed a two-phase, constraint programming approach, first identifying a solution that designates the participants and schedules each of the competitions, then assigning each competitor as the “home” or the “away” team (Russell and Urban 2006).

Rodriguez (2007) presented a constraint programming model for the routing and scheduling of trains running through a junction. The model uses input data from relevant time events of train runs calculated by a simulator. The model can be integrated into a decision support system used by operators who make decisions to change train routes or orders to avoid conflicts and delays (Rodriguez 2007). Li and Li (2007) presented a constraint programming approach to the problem of k-stage hybrid flow-shop scheduling on identical parallel machines with no-wait constraint to minimize makespan (Li and Li 2007).

Monette et al. (2009) introduced a constraint programming approach for the just-in-time job-shop problem where the total earliness and tardiness costs must be minimized. This approach relies on efficient filtering algorithms and intelligent search heuristics. In this paper, they presented a global filtering algorithm based on a machine relaxation and an analysis of the cost evolution under modification of the completion time of activities. The filtering algorithm reduces the bounds of the decision variables, detects precedences between activities, and provides heuristic information for branching in order to improve the lower bound earlier in the search tree. The CP algorithm was then enhanced by a simple local search performed on each solution to get good upper bounds early. Finally, a large neighborhood search was implemented to find high-quality solutions quickly (Monette et al. 2009). Xujun and Zhimin (2009) presented a constraint satisfaction model for the steelmaking-continuous casting scheduling problem solved by constraint programming methods. The problem is described with parallel machines in each processing stage, and the capacity of each machine is limited, and then there are different constraints in the problem, such as process routing constraint, temporal constraint and so on (Xujun and Zhimin 2009).

Zeballos (2010) presented a constraint programming methodology to deal with the scheduling of flexible manufacturing systems. The proposed approach handles several features found in industrial environments, such as limitations on number of tools in the system, lifetime of tools, as well as tool magazine capacity of machines. In addition, it tackles the problem in an integrated way by considering tool planning and allocation, machine assignment, part routing, and task timing decisions altogether in the approach (Zeballos 2010).

Topaloglu and Ozkarahan (2011) first developed a mixed-integer programming model for scheduling residents' duty hours considering the on-call night, day-off, rest period, and total work-hour ACGME (Accreditation Council for Graduate Medical Education) regulations as well as the demand coverage requirements of the residency program. Subsequently, they proposed a column generation model that consists of a master problem and an auxiliary problem. The master problem finds a configuration of individual schedules that minimizes the sum of deviations from the desired service levels for the day and night periods. The formulation of this problem is possible by representing the feasible schedules using column variables, whereas the auxiliary problem finds the whole set of feasible schedules using constraint programming (Topaloglu and Ozkarahan 2011). Edis and Ozkarahan (2011) investigated a resource-constrained identical parallel machine scheduling problem with machine eligibility restrictions. For the considered problem, three optimization models: an integer programming (IP) model, a constraint programming (CP) model and a combined IP/CP model are developed. A problem-based search procedure to be used in CP and IP/CP combined models is also proposed to give quick and efficient results (Edis and Ozkarahan 2011). Liu and Song (2011) proposed a preprocessing approach for solving resource-constrained project-scheduling problems (RCPSP) with integer programming (IP) model, and proved an effective inequality theory for the IP model. The effective inequality can be obtained by solving a maximum clique problem which is built on a sub-network of the original project (Liu and Song 2011).

Lapègue et al. (2012) presented a constraint programming approach to solve a specific scheduling problem arising in a company specialized in drug evaluation and pharmacology research. The aim is to build employee timetables covering the demand given by a set of fixed tasks. The optimality criterion concerns the equity of the workload sharing. A solution to this problem is the assignment of all tasks whose resulting working shifts respect tasks requirements as well as legal and organizational constraints (Lapègue et al. 2012). Zhang et al. (2012b) presented a mathematical model and a solution approach to solve the hot rolling scheduling problem. The problem is formulated as a constraint satisfaction problem with various process constraints, and the mathematical model is established by constraint programming conveniently. The purpose of this research is to find a slab sequence in any given slab set. In order to reduce the complexity of solving the problem and improve the solution efficiency, the original problem is divided into two sub-problems: slab-choose problem and slab-sequence problem. The slab-sequence stage is to sort the slabs from the result of the slab-choose stage (Zhang et al. 2012b).

Unsal and Oguz (2013) presented a constraint programming model for the quay crane scheduling problem (QCSP), which occurs at container terminals, with realistic constraints such as safety margins, travel times and precedence relations. Next, QCSP with time windows and integrated crane assignment and scheduling problem, are discussed (Unsal and Oguz 2013). Pessoa et al. (2013) presented an allocation heuristics within APS (advanced planning and scheduling) systems by employing time windows of the batches regarding constraints in the production programming with delivery dates for end products.

Novas and Henning (2014) presented a novel approach to address the scheduling of resource-constrained flexible manufacturing systems (FMSs). The proposal consists in a constraint programming (CP) formulation that simultaneously takes into account the following sub-problems: machine loading, manufacturing activities scheduling, part routing, machine buffer scheduling, tool planning and allocation, and AGV scheduling, considering both the loaded and the empty movements of the device. Before introducing the model, this work points out the problems that might appear when all these issues are not concurrently taken into account. Then, the FMS scheduling model is presented and later assessed through several case-studies (Novas and Henning 2014). Tang et al. (2014) used the linear scheduling method and constraint programming techniques for solving schedule control problems faced during railroad construction. The proposal comprises a schedule control model, scheduling model, and schedule control system; the scheduling model is central to the schedule control model. Characteristics such as high flexibility and practicality facilitate multi-objective optimization during scheduling and modification of the linear schedule (Tang et al. 2014).

Goel et al. (2015) proposed a constraint programming approach for the optimization of inventory routing in the liquefied natural gas industry. They presented two constraint programming models that rely on a disjunctive scheduling representation of the problem. They also proposed an iterative search heuristic to generate good feasible solutions for these models (Goel et al. 2015). Even et al. (2015) proposed a constraint-based scheduling model that optimizes the evacuation flow rate (number of vehicles sent at regular time intervals) and evacuation phasing of widely populated areas, while ensuring a non-preemptive evacuation for each residential zone. Two optimization objectives are considered: (1) to maximize the number of evacuees reaching safety and (2) to minimize the overall duration of the evacuation (Even et al. 2015).

Zarandi et al. (2016) considered a scheduling problem of minimizing the total of the earliness, tardiness and the number of preemption for the outbound trucks on a cross-dock system. In this paper, they proposed a new multi-criteria model, with non-linear terms and integer variables, which cannot be solved efficiently for large sized problems. They also showed how to map a JIT cross-dock model to a constraint satisfaction problem (CSP) and integer programming (IP). To solve the model for real size applications, a genetic algorithm (GA) is applied (Zarandi et al. 2016). Novara et al. (2016) introduced an efficient constraint programming (CP) model that copes with large-scale scheduling problems in multiproduct multistage batch plants. It addresses several features found in industrial environments, such as topology constraints, forbidden product-equipment assignments, sequence-dependent changeover tasks, dissimilar parallel units at each stage, limiting renewable resources and multiple-batch orders, among other relevant plant characteristics (Novara et al. 2016).

Pour et al. (2018) presented a mixed integer optimization model for the preventive signal maintenance crew scheduling problem in the Danish railway system. The problem contains many practical constraints, such as temporal dependencies between crew schedules, the splitting of tasks across multiple days, crew competency requirements and several other managerial constraints. They proposed a novel hybrid framework using constraint programming to generate initial feasible solutions to feed as 'warm start' solutions to a mixed integer programming solver for further improvement (Pour et al. 2018). Gökgür et al. (2018) presented constraint programming models that aim to solve scheduling and tool assignment problems in parallel machine environments. There are a number of jobs to be processed on parallel machines. Each job requires a set of tools, but limited number of tools are available in the system due to economic restrictions. The problem is to assign the jobs and the required tools to machines and to determine the schedule so that the makespan is minimized. In this paper, three constraint programming models were developed and compared with the existing methods described in the literature (Gökgür et al. 2018). Table 14 summarizes the researches have been done in scheduling with constraint programming.

6.1 Strengths and weaknesses of constraint programming

In this subsection, a summary of the strengths and weaknesses of constraint programming is presented (van Hoeve 2005; Baptiste and Le Pape 2012; Yoon 2006).

6.1.1 Strengths of constraint programming

- Constraint programming allows more flexible modeling language, which is more intuitive and closer to natural language.
- Constraint Programming is declarative: as a result, description of a problem to be solved can be concentrated upon without supposing the specific method to solve a problem.
- Powerful domain filtering algorithm for global constraints.
- Constraint programming can model special "structured" variable types. One example is activities or interval variables that are appropriate to model the scheduling and sequence problem.
- Advanced search strategies.
- Very effective on complex scheduling problem.

6.1.2 Weaknesses of constraint programming

- The efficiency of constraint programming is still unpredictable and intuition is often the most important part of the decision about when and how to use constraints in CP.
- The search algorithms available for solving CP are relatively unsophisticated.
- A lower bound may not be founded by constraint programming.

7 Conclusion

The intelligent scheduling is one of the momentous issues in the domain of scheduling research. It attracts the attention of many researchers for approximately half of a century. This paper has presented a comprehensive review of intelligent scheduling techniques over the last 40 years highlighting their corresponding strengths and weaknesses. In this study, we examined the intelligent scheduling in five areas: fuzzy logic, expert systems, machine learning, stochastic local search optimization algorithms, and constraint programming. Most of the best performing methods were described and the properties of the various artificial intelligence techniques used in solving the scheduling problems have been surveyed. We have investigated about 540 papers on intelligent scheduling that have appeared since 1980.

Table 14 Scheduling with constraint programming (CP)

Nos.	Authors	Years	Application or method	References
1	Weil et al.	1995	Constraint programming for nurse scheduling	Weil et al. (1995)
2	Abdennadher and Schlenker	1999	Nurse scheduling using constraint logic programming	Abdennadher and Schlenker (1999)
3	Guerinik and Van Caneghem	1995	Crew scheduling problems by constraint programming	Guerinik and Van Caneghem (1995)
4	Schaerf	1999	Scheduling sport tournaments using constraint logic programming	Schaerf (1999)
5	Harjunkoski	2000	Scheduling and combinatorial optimization problems using hybrid mixed-integer/constraint logic programming	Harjunkoski et al. (2000)
6	Le Pape and Baptiste	1997	Constraint programming library for preemptive and non-preemptive scheduling	Le Pape and Baptiste (1997)
7	Harjunkoski and Grossmann	2001	Scheduling of multistage batch processes using combined MILP-CP	Harjunkoski and Grossmann (2001)
8	Harjunkoski and Grossmann	2002	Multistage scheduling problems using mixed-integer and constraint programming	Harjunkoski and Grossmann (2002)
9	Chan and Hu	2002	Constraint programming approach to precast production scheduling	Chan and Hao (2002)
10	Timpe	2002	Planning and scheduling problems with combined integer programming and CP	Timpe (2002)
11	Yun and Gen	2002	Preemptive and non-preemptive scheduling using constraint programming	Yun and Gen (2002)
12	Bourdais	2003	Staff scheduling in health care using constraint programming	Bourdais et al. (2003)
13	Kuchcinski and Wolinski	2003	Scheduling of complex behaviors based on hierarchical conditional dependency graphs and constraint programming	Kuchcinski and Wolinski (2003)
14	Del Valle et al.	2003	Selecting and scheduling assembly plans using constraint programming	Valle et al. (2003)
15	Zebullos and Henning	2003	Multi-stage batch scheduling problem using constraint programming	Zebullos and Henning (2003)

Table 14 continued

Nos.	Authors	Years	Application or method	References
16	Elkhyari et al.	2004	Constraint programming for dynamic scheduling problems	Elkhyari et al. (2004)
17	Aggoun and Vazacopoulos	2004	Sports scheduling and timetabling problems with constraint programming	Aggoun and and (2004)
18	Kovács and Váncza	2004	Completable partial solutions in CP and constraint-based scheduling	Kovács and Váncza (2004)
19	Mladenovic et al.	2004	Train scheduling using constraint programming	Mladenovic et al. (2004)
20	Geske	2005	Railway scheduling with declarative constraint programming	Geske (2005)
21	Sevaux et al.	2005	Combining constraint programming and memetic algorithm for the hybrid flow-shop scheduling problem	Sevaux et al. 2005)
22	Li et al.	2005	Steelmaking-making process scheduling using constraint programming	Li et al. (2005)
23	Quiroga et al.	2005	Tool allocation and resource scheduling in FMS using constraint programming	(Quiroga et al. 2005)
24	He	2005	Parallel machine scheduling problem using a CP and tabu search hybrid approach	(He (2005)
25	El Khayat et al.	2006	Integrated production and material handling scheduling using mathematical programming and constraint programming	Khayat et al. (2006)
26	Russell and Urban	2006	Scheduling sports competitions over several venues using constraint programming	Russell and Urban (2006)
27	Trilling et al.	2006	Nurse scheduling using integer linear programming and constraint programming	Trilling et al. (2006)
28	Gomes et al.	2006	Constraint programming for distributed planning and scheduling	Gomes et al. (2006)
29	Rodriguez	2007	Constraint programming for real-time train scheduling at junctions	Rodriguez (2007)
30	Limtanyakul and Schwiegelshohn	2007	Scheduling tests on vehicle prototypes using constraint programming	Limtanyakul and and (2007)

Table 14 continued

Nos.	Authors	Years	Application or method	References
31	Li and Li	2007	No-wait hybrid flowshop scheduling based on constraint programming	Li and Li (2007)
32	Malik et al.	2008	Optimal basic block instruction scheduling for multiple-issue processors using CP	Malik et al. (2008)
33	Garrido et al.	2008	Planning and scheduling in an e-learning environment using constraint programming	Garrido et al. (2008)
34	Watson and Beck	2008	Job-shop scheduling problem using a hybrid CP/local search approach	Watson and Christopher Beck (2008)
35	Liess and Michelon	2008	Constraint programming approach for resource-constrained project scheduling	Liess and Michelon (2008)
36	Benini et al.	2008	Constraint programming for allocation and scheduling on the cell broadband engine	Benini et al. (2008)
37	Monette et al.	2009	Just-in-time scheduling with constraint programming	Monette et al. (2009)
38	Thiruvady et al.	2009	Hybridizing beam-aco with CP for single machine job scheduling	Thiruvady et al. (2009)
39	Garrido et al.	2009	Constraint programming for planning: from plan scheduling to plan generation	Garrido et al. (2009)
40	Xujun and Zhimin	2009	Steelmaking-continuous casting scheduling based on constraint programming	Xujun and Zhimin (2009)
41	Zeballos	2010	Tool allocation and production scheduling in flexible manufacturing systems using constraint programming	Zeballos (2010)
42	Zeballos et al.	2010	Integrated constraint programming scheduling approach for automated wet-etch stations in semiconductor manufacturing	Zeballos et al. (2010)
43	Berthold et al.	2010	Constraint integer programming for resource-constrained project scheduling	Berthold et al. (2010)

Table 14 continued

Nos.	Authors	Years	Application or method	References
44	Zeballos et al.	2010	Constraint programming for the scheduling of flexible manufacturing systems with machine and tool limitations	Zeballos et al. (2010)
45	Novas and Henning	2010	Reactive scheduling framework based on domain knowledge and CP	Novas and Henning (2010)
46	Topaloglu and Ozkarahan	2011	Medical resident scheduling using a CP-based solution approach	Topaloglu and Ozkarahan (2011)
47	Beck et al.	2011	Combining constraint programming and local search for job-shop scheduling	Beck et al. 2011)
48	Zibran and Roy	2011	Conflict-aware optimal scheduling of prioritized code clone refactoring using CP	(Zibran and Roy 2011)
49	Edis and Ozkarahan	2011	Resource-constrained parallel machine scheduling using a combined integer/constraint programming approach	Edis and Ozkarahan (2011)
50	Liu and Song	2011	Combination of constraint programming and mathematical programming for resources-constrained project-scheduling	Liu and Song (2011)
51	Edis and Oguz	2011	Lagrangian-based constraint programming for parallel machine scheduling	Edis and Oguz (2011)
52	Novas and Henning	2012	Rolling horizon-based scheduling of automated wet-etch stations using CP	Novas and Henning (2012)
53	Limtanyakul and Schwiegelshohn	2012	Improvements of constraint programming and hybrid methods for scheduling of tests on vehicle prototypes	Limtanyakul and Schwiegelshohn (2012)
54	Öztürk et al.	2012	Balancing and scheduling of flexible mixed model assembly lines with parallel stations using constraint programming	Öztürk et al. (2012)
55	Lapègue et al.	2012	Tour scheduling problem with fixed jobs using constraint programming	Lapègue et al. (2012)
56	Zhang et al.	2012	Hot strip rolling scheduling based on constraint programming	Zhang et al. (2012)
57	Unsal and Oguz	2013	Quay crane scheduling problem using constraint programming	Unsal and Oguz (2013)

Table 14 continued

Nos.	Authors	Years	Application or method	References
58	Heinz et al.	2013	Resource allocation and scheduling using constraint integer programming	Heinz et al. (2013)
59	Pessoa et al.	2013	Advanced planning and scheduling systems based on time windows and CP	Pessoa et al. (2013)
60	Novas and Henning	2014	Integrated scheduling of resource-constrained flexible manufacturing systems using constraint programming	Novas and Henning (2014)
61	Zhao and Li	2014	Scheduling elective surgeries using constraint programming	Zhao and Li (2014)
62	Tang et al.	2014	Schedule control model for linear projects based on linear scheduling method and constraint programming	Tang et al. (2014)
63	Goel et al.	2015	Constraint programming for LNG ship scheduling and inventory management	Goel et al. (2015)
64	Wang et al.	2015	Scheduling operating theatres using mixed-integer and constraint programming	Wang et al. (2015)
65	Even et al.	2015	Non-preemptive evacuation scheduling using constraint programming	Even et al. (2015)
66	Zarandi et al.	2016	Scheduling of JIT cross-docking systems using constraint programming	Zarandi et al. (2016)
67	Novara et al.	2016	Large-scale scheduling problems in multiproduct multistage batch plants using CP	Novara et al. (2016)
68	Hashemi Doulabi et al.	2016	Operating room planning and scheduling using a constraint programming based branch and price and cut approach	Doulabi et al. (2016)
69	Booth et al.	2016	Multi-robot task allocation and scheduling in retirement homes using CP	Booth et al. (2016)
70	Carlsson et al.	2017	Scheduling double round-robin tournaments with divisional play using CP	Carlsson et al. (2017)
71	Novara and Henning	2017	Scheduling of multiproduct multistage batch plants using constraint programming	Novara and Henning (2017)

Table 14 continued

Nos.	Authors	Years	Application or method	References
72	Gedik et al.	2018	Unrelated parallel machine scheduling using constraint programming	Gedik et al. (2018)
73	Pour et al.	2018	A hybrid constraint programming/mixed integer programming framework for preventive signaling maintenance crew scheduling	Pour et al. (2018)
74	Ham	2018	Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming	Ham (2018)
75	Tang et al.	2018	Scheduling optimization of linear schedule with constraint programming	Tang et al. (2018)
76	Gökgür et al.	2018	Parallel machine scheduling using constraint programming	Gökgür et al. (2018)

According to our investigation, the number of papers being published in intelligent scheduling has been steadily raising over the past few decades. It demonstrates the capabilities of artificial intelligence methods in scheduling problems and clearly needs to better understand the potential of artificial intelligence techniques, like machine learning, for performing scheduling operations.

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