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A research survey: review of AI solution strategies of job shop scheduling problem

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Abstract This paper focus on artificial intelligence approaches to NP-hard job shop scheduling (JSS) problem. In the literature successful approaches of artificial intelligence techniques such as neural network, genetic algorithm, multi agent systems, simulating annealing, bee colony optimization, ant colony optimization, particle swarm algorithm, etc. are presented as solution approaches to job shop scheduling problem. These studies are surveyed and their successes are listed in this article.

Keywords Artificial intelligence · Scheduling · Metaheuristic

Introduction

The scope and the purpose of this paper are to present a survey of job shop scheduling problems (JSSs) using artificial intelligence (AI) solution techniques which covers the AI strategies for different objective function of job shop scheduling problem. Numerous approaches have been investigated and classifications of these techniques are given.

The remainder of the study is as follows: JSS problem is defined in detail in section "Job shop scheduling problem", history and structure of AI mentioned in section "Brief history of AI". In section "AI strategies for job shop problem" provides a detailed classification according to the survey. In section "Analysis and discussions", some conclusions and future research road maps are given. Selected time period is between 1997 and 2012. Articles are selected mainly from Science Direct and EBSCO data bases.

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Job shop scheduling problem

Job shop scheduling problem (JSS) consists of a finite jobs set, J_i (i = 1,2,…,n) to be processed on a finite machine set M_k (k = 1,2,…,m) (Geyik and Cedimoglu 2004). According to its production routine, each job is processed on machines with a given processing time, and each machine can process only one operation for each job (Chen et al. 2012). JSS can be thought of as the allocation of resources over a specified time to perform a predetermined collection of tasks (Surekha and Sumathi 2011). In other words, the production scheduling problem allocates limited resources to tasks over time and determines the sequence of operations so that the constraints of the system are met and the performance criteria are optimized (Akyol and Bayhan 2007).

The job shop scheduling problem is one of the most important and complicated problems which has been known as an NP-hard and very challenging combinatorial optimization problem since 1950s (Lenstra et al. 1977; Zhang et al. 2013) in machine scheduling. The high complexity of the problem makes it hard to find the optimal solution within reasonable time in most cases (Asadzadeh and Zamanifar 2010).

JSS can be applied to the manufacturing processes and affects really the production time and the cost of production for a plant (Lin et al. 2010). Solving JSS enables a manufacturer's ability to be more competitive. Therefore, AI techniques are developed to solve JSS problem.

Brief history of AI

The field of artificial intelligence (AI) research was founded at a conference on the campus of Dartmouth College in the summer of 1956 (Crevier 1993) and AI is the generic name given to the field of computer science dedicated to the development of programs that attempt to replicate human intelligence (Fonseca and Navaresse 2002). If too many tasks are allocated to the system, the human does not have opportunities to build up a mental model of the system. As a result, exceptions which the system is not able to handle cannot be solved by the human either (Wiers 1997). So AI can be described as "the study and design of intelligent agents" (Russell and Norvig 2003).

By the use of AI techniques, researchers were able to develop clever methods to solve NP hard problems such as JSS. Solution quality obtained by AI techniques is much better than Branch-and-Bound based heuristic solutions for JSS and solution time is much shorter.

Some early milestones include work in problems solving which included basic work in learning, knowledge representation, and inference as well as demonstration programs in language understanding, translation, theorem proving, associative memory, and knowledge-based systems (Buchanan 2005).

The artificial intelligence (AI) research community has been very active in the area of planning and scheduling since the 1960s (Spyropoulos 2000) and early history of AI is summarized by Russell and Norvig (2003) as; (1) McCulloch and Pitts: Boolean circuit model of brain (1943). (2) Turing's "Computing Machinery and Intelligence" (1950). (3) Look, Ma, no hands! (1952–1969). (4) Early AI programs, including Samuel's checkers program, Newell and Simon's Logic Theorist, Gelernter's Geometry Engine (1950s). (5)Dartmouth meeting: "Artificial Intelligence" adopted (1956). (6) Robinson's complete algorithm for logical reasoning (1965). (7) AI discovers computational complexity. Neural network research almost disappears (1966–1974). (8) Early development of knowledge-based systems (1969–1979). (9) Expert systems industry booms (1980–1988). (10) Expert systems industry busts: "AI Winter" (1988–1993). (11) Neural networks return to popularity (1985–1995). (12) Resurgence of probabilistic and decision-theoretic method Rapid increase in technical depth of mainstream AI "Nouvelle AI": ALife, GAs, soft computing (1988).

After this time period, Meta heuristic techniques are used to find near optimal solution for scheduling problems.

AI strategies for job shop problem

In this survey, recent studies on job shop scheduling problems are summarized based on problem objective function and used AI techniques to solve JSS. Table 1 list the well-known objective functions of JSS.

Table 1 Well known objective functions (Ross and Corne 2005)

Objective function	Symbol	Interpretation
Maximum complete time	$C_{\max}$	The cost of a schedule depends on how long the processing system is devoted to the entire set of jobs
Mean complete time	$\bar{C}$	The schedule's cost is directly related to the average time it takes to finish a single job
Maximum flow time	$F_{\max}$	The cost is directly related to the longest job
Mean flow time	$\bar{F}$	The cost is directly related to the average time it takes to process a single job
Maximum lateness	$L_{\max}$	The schedule's costs are directly related to its latest job
Mean lateness	$\bar{L}$	The cost is directly related to the average difference between complete times and due-dates for all jobs. Early jobs in effect contribute reward, due to negative differences
Maximum tardiness	$T_{\max}$	The cost is directly related to the latest job that completes after its due-date
Mean tardiness	$\bar{T}$	A schedule's cost is directly related to the average lateness for all jobs, where early jobs are considered to have a late time of 0
Number of tardy jobs	$\sum U_j$	The schedule's cost depends on the number of jobs that complete after their due date
Maximum earliness	$E_{\max}$	A schedule's cost is directly relatedto the earliest job that completes before its due-date

Genetic algorithm (GA)

The term of genetic algorithm was first used by Holland (1975) and take place in literature universally, early studies and applications of GA are displayed in some books such as those by Davis (1991) and Chambers (2001). Work on genetic algorithms (GA) for solving the JSS including the FSP has a history of almost four decades (Davis 1985; Liepins and Hilliard 1987; Cleveland and Smith 1989) and (Nakano and Yamada 1991). Recent studies of GA on Job shop scheduling problem are listed in Table 2.

Beam search (BS)

Beam search is a heuristic method which explores a graph by expanding the most promising node in a limited set. This search technique was primarily used in artificial intelligence for the speech recognition problem (Lowerre 1976). Ow and

Table 2 Genetic algorithm

Objective function	Explanation of study	Algorithm/ industry	Article
Mean flowtime	In their experimental results that the capabilities of genetic algorithms vanish with an increasing problem size, and they are not efficient to find a near-optimal solution in a reasonable time	Algorithm	Bierwirth and Mattfeld (1999)
Makespan	Proposed a hybrid genetic algorithm, based on a genetic algorithm and heuristic rules, for the problem of $J\|S_{ij}\|C_{max}$ (set-up times are sequence-dependent constraint). Computational analysis show that proposed hybrid algorithm is superior to earlier methods proposed for the same problem	Algorithm	Cheung and Zhou (2001)
Mean job tardiness and mean job cost	The solution of genetic algorithms was compared to several common dispatching rules. The results indicated that the performance of genetic algorithms is significantly superior to that of the common dispatching rules	Algorithm	Chryssolouris and Subramaniam (2001)
Makespan	Two new approaches to solve jointly the assignment and job-shop scheduling problems (with total or partial flexibility) is presented. The first one is the approach by localization (AL). The second one is an evolutionary approach controlled by the assignment model (generated by the first approach). Two examples are presented to show the efficiency of the two suggested methodologies	Algorithm	Kacem et al. (2002)
Makespan	An efficient solution representation strategy is suggested to easily check the constraints and avoid repair mechanism	Algorithm	Ombuki and Ventresca (2004)
Mean job tardiness, mean flowtime, maximum tardiness, mimization of the weighted number of tardy jobs	In two recent papers 24 problems of the benchmark set have been investigated, new best solutions have been found for 13 of 24 problems while the computational burden is cut significantly	Algorithm	Mattfeld and Bierwirth (2004)
Makespan	Modified genetic algorithm with search area adaptation (mGSA) is proposed for solving the job-shop scheduling problem. As a result of numerical experiments by using two benchmark problems, it is shown that this method has better performance than existing GAs	Algorithm	Watanabe et al. (2005)
Makespan	A hybrid genetic algorithm for the job shop scheduling problem is proposed. After a schedule is obtained, a local search heuristic is applied to improve the solution. The computational results show that the algorithm produced optimal or near-optimal solutions on all instances tested	Algorithm	Gonçalves et al. (2005)
Makespan	An adaptive genetic algorithm is proposed for distributed scheduling problems in multi-factory and multi-product environment. Five multi-factory models have been solved by different well known optimization approaches. The results shows that significant improvement could be obtained by the proposed algorithm	Algorithm	Chan et al. (2005)
Late cost, inventory cost	A GA-based approach has been developed and proposed to solve Assembly job shop problem with Lot Streaming technique The experiment results suggest that minimum slack time (MST) with equal size (ES) mode or MST-ES surpasses the others in terms of two performance measures, i.e. the minimum cost obtained in most of the test problems, and the average cost obtained over all test problems. This study may provide some useful insights about the application of GA to solve lot streaming and assembly job shop problem simultaneously	Algorithm	Chan et al. (2008)
Makespan	Based on an extensive computational study shows that new algorithm outperforms other known GA for the same problem, and gives results comparable with the best algorithm known so far	Algorithm	Pezzella et al. (2008)
Penalty cost, setup cost, makespan	An innovative approach was proposed to solve lot streaming (LS) problems by determining the LS conditions (the split lots, the sub-lot number and the sub-lot size) and the sub-lot processing sequence using GAs. Illustrative experiments have shown that the proposed model can defeat the existing company policy for problems with m = 5–6 and n =1 0–30 under all tested conditions	Industry	Chan et al. (2009)

Table 2 continued

Objective function	Explanation of study	Algorithm/ industry	Article
Total lateness	An innovative GA-based approach has been developed and proposed to solve resource-constrained assembly job shop scheduling with lot streaming (LS) technique. An experiment has been launched to investigate the performance differences between GA and PSO. Based on the same working mechanism, GA and PSO have been compared on a number of test problems. Computational results suggested that Equal Size is always the best LS strategy	Algorithm	Wong et al. (2009)
Tardiness	A hybrid framework that integrates individual heuristics with a genetic algorithm for job-shop scheduling to minimize weighted tardiness. However, it is not as good as the method by Kreipl (2000), a method specifically designed for minimizing weighted tardiness in a job-shop. The hybrid GA outperforms the GA in Mattfeld and Bierwirth (2004) in a majority of the test cases	Algorithm	Zhou et al. (2009)
Average transfer time Fw	An adaptive annealing genetic algorithm (AAGA), and computational results proved AAGA was more efficient than traditional GA	Algorithm	Liu et al. (2011)
Makespan	For a flexible multi- product, parallel machine sheet metal job shop with an objective of minimizing makespan, proposed GA find better solutions than other simple sequencing rules. An option of job-splitting among the parallel machines is also provided. A genetic algorithm is embedded in the simulator to find the optimal solution	Industry	Chan et al. (2011)
Earliness and Tardiness	Developed a new meta heuristic method which combines GA, local search, and Branch & Bound Algorithm. The computational results show that the deviation of the meta-heuristics solutions from the optimal one is very small, which confirms the effectiveness of meta-heuristics as a new approaches for solving hard scheduling problems	Algorithm	Rebai et al. (2012)
Makespan	A mixed selection operator based on the fitness value and the concentration was designed in order to increase the diversity of the population. A local search operator was designed in order to improve the quality of the solutions. The experimental results show that the proposed algorithm is effective and performs better than the compared algorithms (Sabuncuoglu and Gurgun 1996; Yang et al. 2008; Wang and Zheng 2001	Algorithm	Qing-dao-er-ji and Wang (2012)
Makespan	GA is tested on 22 benchmark problems and is compared with simulated annealing (Kirkpatrick et al. 1983) and similar particle swarm optimization algorithm (Lian et al. 2006). The comparative results show the promising advantage of GA on stochastic scheduling	Algorithm	Lei (2012b)
Fuzzy makespan	Computational results show that co-evolutionary genetic algorithm (CGA) has better performance than decomposition-integration genetic algorithm (DIGA), PEGA and particle swarm optimization and simulated annealing (PSO+SA)	Algorithm	Lei (2012a)
Makespan	Genetic algorithm, adaptive learning, and heuristics into a sequential genetic algorithm are integrated, and consequently obtain highly satisfactory schedules within a short period of time	Industry	Huang et al. (2012)
Total tardiness, total machine idle time, and makespan	The results indicate that the proposed method using GGA and GA can better assign a machine to an operation and better arrange the sequence of operations at each machine to achieve lower tardiness, machine idle time, and makespan than weapon production scheduling (WPS) (Chen et al. 2008) does	Algorithm	Chen et al. (2012)

Morton (1988) and Scheduling (1995) provide detail explanation of Beam Search method. One application of beam search is solving JSS problem is given in Table 3.

Tabu search (TS)

Tabu search is a heuristic method which is originally proposed by Glover (1986). Tabu Search is a neighborhood search method which employs "intelligent" search and flexible memory technique to avoid being trapped at local optimum. Tabu search enhances the performance of these techniques by using memory structures that describe the visited solutions or user-provided sets of rules (Glover 1989). Recent studies of TS are listed in Table 4.

Agent based systems (ABS)

An intelligent agent receives messages from the environment via its perception mechanism. These messages are then evaluated by the cognition system and appropriate actions are produced and implemented by the action module (Aydın and Oztemel 2000). The word "agent" is first used in John H. Miller's 1991 paper "Artificial Adaptive Agents in Economic Theory" (Holland and Miller 1991) which is based on an

Table 3 Beam search

Objective function	Explanation of study	Algorithm/ industry	Article
Makespan and mean tardiness	The beam search method is a very good heuristic for the job shop problems. As compared to other algorithms, the speed and the performance of a beam search based algorithm are manipulated by changing search parameters and evaluation functions. Coding of the algorithm is very simple and hence it can easily be implemented by practitioners	Algorithm	Sabuncuoglu and Bayiz (1999)

Table 4 Tabu search

Objective function	Explanation of study	Algorithm/ industry	Article
Makespan	Several results for the multiprocessor job-shop scheduling (MSJ) problem have been presented in this paper. Computational experiments were conducted on three different sets of test problems. Authors state that this integrated procedure seems to be superior to prior heuristics for the MJS problem, and has quite satisfying results on classical job-shop scheduling problems as well	Algorithm	Peres and Paulli (1997)
Makespan	An effective two-phase tabu search algorithm is proposed for flexible job shop scheduling with sequence dependent setups. Computational results show that the proposed algorithm generates good quality solutions, comparable to the branch and bound method, very quickly. As a result it is concluded that the proposed algorithm can attain the optimal solution for a flexible job shop scheduling problem with sequence dependent setups in very little time	Algorithm	Mehrabad and Fattahi (2007)

Table 5 Agent based systems

Objective function	Explanation of study	Algorithm/ industry	Article
Flowtime and tardiness	The higher frequency of learning may help an agent to quickly adapt to variations on the shop floor	Algorithm	Pendharkar (1999)
Mean tardiness	The system is composed of the agent and the simulated environment (SE). The agent is able to perform dynamic scheduling based on the available information provided by the SE. It makes decision for selection of the most appropriate dispatching rule in real time. At the end of training, the agent gives better results than the traditional alternatives (SPT, COVERT, and CR rules)	Algorithm	Aydın and Oztemel (2000)
Makespan	A parallel implementation of modular simulated annealing algorithm (MSA) is presented. In order to run the parallel MSA, multi agent systems is used. The empirical results show that the method is quite successful comparing to the sequential version of MSA	Algorithm	Aydın and Fogarty (2004)
Number of tardy job	An experimental approach for performance analysis of a multi-agent system for job routing in job-shop settings. Some simple but practical mechanisms are proposed and implemented	Algorithm	Usher (2003)
Total tardiness	Neural reinforcement learning method is used and the empirical evaluation on large-scale benchmark problems leads to the conclusion that problems of current standards of difficulty can very well be effectively solved by the learning method. A disadvantage of this reactive scheduling approach is the fact that only non-delay schedules can be produced, which in many cases prohibits finding optimal schedules	Algorithm	Gabel and Riedmiller (2007)
Makespan	The simulation results show that the principle of the algorithms is simple, their computational quantity is small, and the algorithms can be applied to multi-batch dynamic scheduling with unpredictable entry time due to their favorable potential. It is suitable for multi-objective scheduling problems that need to consider average delay time and delivery cut-off time. The scheduling results of wasp colony algorithms are better than those of static scheduling algorithms for divided scheduling batch by batch	Algorithm	Cao et al. (2009)

Table 6 Ant colony algorithm

Objective function	Explanation of study	Algorithm/ industry	Article
Total weighted tardiness	They proposed an ant colony algorithm and showed by computational analysis that it performs better than a genetic algorithm	Algorithm	Nait Tahar et al. (2005)
Makespan	An ant colony optimization which represents a challenging approach to the scheduling of FMSs including alternative machine tools, setup and transportation times is proposed. It is able to tackle stagnation and to offer a real-time performance with respect to the compared GA-based system	Algorithm	Rossi and Dini (2007)
Makespan	ACO is an easy algorithm to implement, with roughly the same amount of code and difficulty as that of a genetic algorithm. ACO is a good example of how harnessing, mimicking and utilizing processes occurring in nature for tough scientific problems can be a successful enterprise	Algorithm	Heinonen and Pettersson (2007)
Makespan	The proposed algorithm has been tested on 101 benchmark instances and compared with other algorithms. The solutions ant colony optimization combined with taboo search (ACOFT) can yield are often the same or slightly better than reported for best-performing algorithms for the JSSP	Algorithm	Huang and Liao (2008)
Makespan	Proposed ACO algorithm provided results compared to genetic algorithm for solving JSS	Algorithm	Surekha and Sumathi (2010)
Sum of material processing cost, setup time cost and inventory cost	In the small problems, this study used LINGO to obtain the optimal solution and confirm the efficiency of ACO. The effectiveness exceeds 88 %. For production managers, these approximate optimal solutions can provide enterprises with satisfactory production schedules in a short time	Algorithm	Huang (2010)
Makespan	Knowledge based ant colony optimization (KBACO) outperforms these eight published algorithms; 1. Temporal Decomposition, 2. Controlled Genetic Algorithm (CGA), 3. Approach by Localization (AL), 4. AL+CGA, 5. PSO+SA, 6. Tabu Search, 7. GENACE, 8. KBACO	Algorithm	Xing et al. (2010)

earlier conference presentation of the same authors. Recent studies of ABS are listed in Table 5.

Ant colony optimization (ACO)

The work of Goss, Aron, Deneubourg and Pasteels on the collective behavior of Argentine ants, provided the idea of Ant colony optimization algorithms (Goss et al. 1989). First ACO proposed by Dorigo (1992) in his PhD thesis to search for an optimal path in a graph depends on the behavior of ants seeking a path between their colony and source food (Colorni et al. 1991; Dorigo 1992). Recent studies of ACO on JSS are listed in Table 6.

Neural network (NN), artificial neural network (ANN)

Artificial neural systems or neural networks are physically cellular systems which can acquire, store and utilize experimental knowledge (Zurada 1992) artificial neural networks (ANNs) have been successfully applied to solve a variety of problems (Sabuncuoglu and Gurgun 1996). For detail information about application of neural network refer to the Zhang and Huang (1995). Recent studies of NN on JSS are listed in Table 7.

Particle swarm algorithm (PSO)

Particle swarm optimization (PSO) is developed by Kennedy and Eberhart (Kennedy and Eberhart 1995). The position of one particle corresponds to a solution of the problem. Like a bird that fies to the food, in PSO, one particle moves its position to a better solution according to the best particle's experience and its own experience (Lin et al. 2010). Recent studies of PSO method on job shop scheduling problem are listed in Table 8.

Variable neighborhood search (VNS)

Variable neighborhood search (VNS) proposed by Mladenovi'c and Hansen in (1997) as a metaheuristic method for solving combinatorial optimization, and global optimization problems. For detail information about method and applications refer to Hansen et al. (2008). Recent studies of VNS method on JSS problem are listed in Table 9.

Fuzzy logic (FL)

The concept of fuzzy logic (FL) was conceived by Lotfi A. Zadeh, introduced the paper on fuzzy sets (Yen and Langari 1999) and presented not as a control methodology but a way of processing data by allowing partial set member-

Table 7 Neural network

Objective function	Explanation of study	Algorithm/ industry	Article
Average lateness	The results obtained by the neural network are better than these obtained either from the fuzzy inference system or from SIPAPLUS. The approach based on an implicit learning from several typical examples gives better results and its performance increases as the number of examples learned by the neural network increases	Algorithm	Geneste and Grabot (1997)
Makespan	A modified *BEP (back-error propagation)* structure is suggested as it is able to deal with much larger and more complex problems than any previous method	Algorithm	Jain and Meeran (1998)
Makespan	This work largely focuses on the problem of resource utilization, For practical implementation, the problem can be extended to involve the temporal relationship on required resources for each job and model is not suitable for large size problems	Algorithm	Huang and Chen (1999)
Total setup cost	An industrial problem is expressed by a nonlinear integer programming model and solved successfully by NN	Industry	Chen and Dong (1999)
Mean machine utilization and mean job tardiness	Metamodel accuracy is affected by various factors. Experiments indicated that metamodel accuracy can decrease rapidly when estimating short-term job tardiness for terminating type systems in the context of stochastic or complex systems. The meta models were successful in discriminating between dispatching policies in this same contexts	Algorithm	Sabuncuoglu and Touhami (2002)
Estimating average flow times	ANN-based simulations were able to fairly capture the underlying relationship between jobs' machine sequences and their resulting average flowtimes	Algorithm	Fonseca and Navaresse (2002)
Makespan	The *purpose* of the research is to design a production activity scheduling system scheduling software that can generate effective job shop schedules using the multi-layered perceptron (MLP) neural networks. The study is limited to the problem of deterministic time-varying demand pattern over a fixed planning horizon	Industry	Feng et al. (2003)
Productivity, inventory level, tardiness, flexibility and stability	Extended technique for order performance by similarity to ideal solution (TOPSIS) was proposed and used for neural fuzzy methodology for schedule assessment (NFMSA). Extended TOPSIS was developed by extending TOPSIS with fuzzy logic and neural networks to deal with linguistic and inaccurate data in the manufacturing environment	Algorithm	Cha and Jung (2003)
Makespan	Successfully developed a NN scheduler, which provides a close approximation to the performance of a GA scheduler for job shop scheduling problems	Algorithm	Weckman et al. (2008)

Table 8 Particle swarm algorithm

Objective function	Explanation of study	Algorithm/ industry	Article
Makespan	The performance of the new approach similar particle swarm optimization algorithm (SPSOA) is evaluated in comparison with the results obtained from GAs for three representative instances, and obtained results show the effectiveness of the proposed approach. The SPSOA proposed in this paper for small size JSSP is very efficacious, but not for large size JSS	Algorithm	Lian et al. (2006)
Makespan	Employed a high global search efficiency of PSO with a powerful ability to avoid being trapped in local minima of SA by introducing an algorithm called hybrid evolutionary algorithm (HEA)	Algorithm	Ge et al. (2007)
Makespan, maximal machine workload and total workload of machines	An effective hybrid particle swarm optimization algorithm is proposed to solve the multi-objective flexible job shop scheduling problems. When compared to the results from the other alternative solution methods, all results could be got in the reasonable computational time. It proves that proposed hybrid algorithm is efficient and effective	Algorithm	Zhang et al. (2009)
Makespan	MPSO is tested and approved with 43 instances that are a standard benchmark taken from the OR-Library. According to the experimental results, MPSO can reach the optimal area in the search space with smaller population size and iterations than other existing algorithms achieved	Algorithm	Lin et al. (2010)
Total cost	The algorithm is very efficient and can solve both deterministic and stochastic demand problems	Algorithm	Varthanan et al. (2012)

Table 9 Variable neighborhood search

Objective function	Explanation of study	Algorithm/ industry	Article
Makespan	A capable and superior metaheuristic algorithm known as VNS (variable neighborhood search) is proposed to solve the problem of scheduling job shop (JSS) where set-up times were sequence-dependent (SDST) on each processor to minimize the maximum completion times of operations or makespan. The computational results verified that the VNS not only dominated other well-known algorithms in terms of both computational time and quality solution but also sustained its robustness in all situations	Algorithm	Roshanaei et al. (2009)
Mean flow time	Estimate proper parameters of their scheduling method at any rescheduling point	Algorithm	Zandieh and Adibi (2010)
Makespan	The results demonstrated that the proposed method is better than other algorithms in the past research	Algorithm	Yazdani et al. (2010)

Table 10 Fuzzy logic

Objective function	Explanation of study	Algorithm/ industry	Article
Fuzzy makespan	In this study, by considering the imprecise or fuzzy nature of the data in real-world problems, job shop scheduling with fuzzy processing time and fuzzy due date is introduced	Algorithm	Sakawa and Kubota (2000)
Flow time and mean tardiness	A new Fuzzy Priority Rule is generated. It decreases flow time by 13 %, mean tardiness by 40 % and WIP by 14 % and increases output by 1 % compared with other priority rules	Algorithm	Canbolat and Gundoğar (2004)
Makespan	The proposed algorithm regenerates the schedule in the case of a machine breakdown, with a small increase in the makespan. The system architecture and linguistic variables are presented and results showed that the proposed algorithm improves the system efficiency	Algorithm	Bilkay et al. (2004)
Fuzzy makespan	The main contribution of this study is to provide an effective path to the problem by GA. In this study, a genetic algorithm approach is developed to minimize a fuzzy makespan	Algorithm	Lei (2012a)

ship rather than crisp set membership or non-membership. Fuzzy logic is an analysis method purposefully developed to incorporate uncertainty into a decision model (Zadeh 1965). Fuzzy logic allows for including imperfect information no matter the cause. Recent studies of FL method on Job shop scheduling problem are listed in Table 10.

Bee colony optimization (BCO)

The bees algorithm is a population-based search algorithm and first study is done by Pham et al. (2005) which performs with random search and a kind of neighbor search method to solve combinatorial optimization problems. Karaboga (2005) studied a new optimization algorithm based on the intelligent behavior of honey bee swarm. From the simulation results, it is concluded that the proposed algorithm can be used for solving unimodal and multi-modal numerical optimization problems. Recent studies of BCO on JSS are listed in Table 11.

Analysis and discussions

Scheduling is one of the most critical issues for manufacturing systems. Due to its NP-hard nature, developing an optimal schedule is very costly and impractical. Therefore many different heuristics are developed for this problem. Among the heuristic approaches, AI techniques provide very good schedules. In this survey, solving AI techniques of different objective function of Job Shop Scheduling problems are summarized covering the last 15 years to put on a road map.

Although there are hundreds of articles related to scheduling, we limit the coverage of this survey to only AI approaches to JSS and used the key words: Genetic Algorithm, Beam Search, Tabu Search, Agent Based Systems, Ant Colony Algorithm, Neural Network, Particle Swarm Algorithm, Variable Neighborhood Search, Fuzzy Logic, and Bee Colony Optimization combined with Job Shop Scheduling. These key words resulted in a couple of hundred articles and we further select 62 of them to complete the survey.

Table 11 Bee colony optimization (BCO)

Objective function	Explanation of study	Algorithm/ industry	Article
Machine utilization and product cycle-time	This paper describes a novel approach that uses the honey bees foraging model. Comparing the performance of peers, bee algorithm performs slightly better than ant algorithm. Bee algorithm achieves better mean and maximum percentages as well as higher number of best solutions in comparison to ant algorithm. The time taken to solve the 82 job shop problems for both heuristics is approximately equal with bee colony being slightly faster	Algorithm	Chong et al. (2006)
Makespan	This study was the first research on the application of artificial bee colony (ABC) algorithm to the FJSP with makespan criterion. ABC performs better than other algorithms on Kacem instances (Kacem and Hammadi 2002) and BRdata problems (Brandimarte 1993) in solving almost all the instances in terms of the best results, average results, and standard derivation	Algorithm	Wang et al. (2012)
Total weighted tardiness	An artificial bee colony (ABC) algorithm based on criticality information for solving job shop scheduling problems is proposed. ABC obtains better result than PSO (particle swarm optimization) for nine instances	Algorithm	Zhang (2011)
Total weighted tardiness	The computational results verify the effectiveness and efficiency of the proposed approach, especially for larger-scale instances	Algorithm	Zhang et al. (2013)

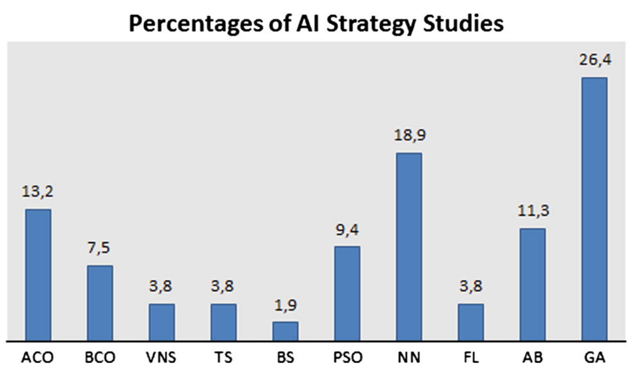

Fig. 1 percentages of AI strategy studies (1997-2012).

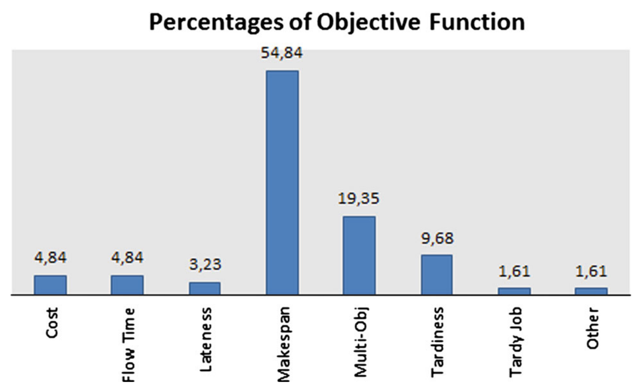

Fig. 2 percentages of objective function (1997-2012).

The search for articles resulted in a large number of articles that uses branch and bound methods in their algorithms. Even though some of them are state-of-the-art algorithms, they are not included in this survey because branch-and-bound is not an AI technique. On the other hand, there exist a few articles that use branch-and-bound method in the context of Beam Search.

Findings from the survey are:

1. After 2000s, while Neural Network techniques are used shown a decrease in literature. Genetic Algorithm, Agent Based Systems and Ant Colony optimization have shown an increase as can be seen in Fig. 1.
2. Most of researchers are focused on minimization of makespan problem and second tier problem is Multi objective problems. Percentage of objective functions of each article is shown in Fig. 2.
3. Most of researchers are focused on Algorithm development. A few articles focus on solving real life industrial problem. Percentage of article types is as seen in Fig. 3.

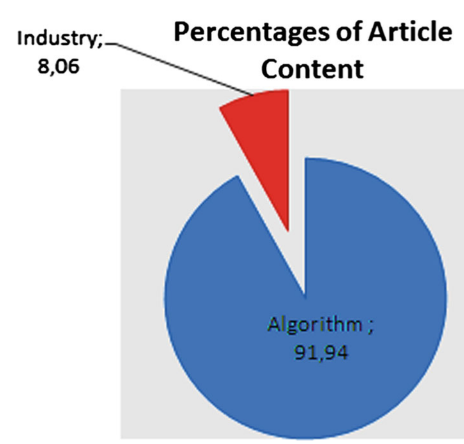

Fig. 3 percentages of article types (1997-2012).

4. None of research shows that which technique is superior to others for this problem.
5. In specific parts, some models are superior to others like;

a. Wu et al. (1991, 1993) compared the performance of genetic algorithms and local search heuristics to generate robust schedules. The results showed the performance of genetic algorithms in generating schedules with much better makespan and stability than local search heuristics.
b. Bierwirth and Mattfeld (1999) reported in their experimental results that the capabilities of genetic algorithms vanish with an increasing problem size, and they are not efficient to find a near-optimal solution in a reasonable time.
c. Cheung and Zhou (2001) compared the performance of a hybrid genetic algorithm, based on a genetic algorithm and heuristic rules, for the problem of $J_m|S_{ij}|C_{max}$ (m machine JSS problem with respect to sequence dependent setup times in order to minimize makespan). They showed by computational analysis that their hybrid algorithm is superior to earlier methods proposed for the same problem.
d. Xing et al. (2010) compared the performance of KBACO (Knowledge based ant colony opt.) for optimal makespan outperforms these eight published algorithms; 1. Temporal Decomposition, 2. Controlled Genetic Algorithm (CGA), 3. Approach by Localization (AL) 4. AL+CGA, 5. PSO+SA, 6. Tabu Search, 7. GENACE.
e. Yazdani et al. (2010) compared the performance of solving FJSP to minimize makespan. The results demonstrated that variable neighborhood search algorithm is better than other algorithms in the past research.
f. Zhang (2011) compared the performance of an artificial bee colony algorithm based on criticality information for solving job shop scheduling problems. ABC obtains better result than PSO for nine instances.
g. Lei (2012b) compared the performance of solving minimizing makespan for scheduling stochastic job shop with random breakdown. Proposed GA is tested on 22 benchmark problems and is compared with simulated annealing (Kirkpatrick et al. 1983) and similar particle swarm optimization algorithm (Lian et al. 2006). The comparative results show the promising advantage of GA on stochastic scheduling.
h. Lei (2012a) compared the performance of co-evolutionary genetic algorithms which has better performance than decomposition integration genetic algorithm (DIGA), PEGA and particle swarm optimization and simulated annealing (PSO+SA).

Conclusions

Job shop scheduling problems are difficult problems to be solved due to their NP-Hard nature. Researchers and practitioners try to develop efficient solutions for these problems during the last couple of decades. With the recent advancement in computing techniques, artificial intelligence techniques becomes a powerful solution approaches to many combinatorial optimization problems including JSS.

In this survey, a range of AI based solution methods are surveyed. Since these methods are not optimization methods, none of the AI techniques guarantees the optimal solution. However, based on solution approaches as mentioned in section "Analysis and discussions", the efficiency of AI techniques to some problems is identified.

Surveyed articles show that most of the works are focused on testing the develop algorithm on benchmark or generated problems.

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