Improving the ISO 9000 Factual Approach Principle through Metaheuristic

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Abstract
In this paper, the efficiency of the factual approach principle to decision making is improved by the mean of an Artificial Bees Colony metaheuristic. This principle is one of the eight basic principles in which the quality management system of the ISO 9000 series is based. This metaheuristic is adapted to solve the Flow-Shop Scheduling Problems with Makespan criterion, and the result proves the efficiency of the factual approach to decision making.
Keywords: data analysis, factual approach to decision making, quality management system, metaheuristic, production scheduling

1. Introduction

The quality management system standards of the ISO 9000 Family is based on eight Quality Management Principles: customer focus, leadership, involvement of people, process approach, system approach to management, continual improvement, factual approach to decision making and mutually beneficial supplier relationships. These management principles will not only facilitate management for users of ISO 9001, but also help in overall performance of the organization.

In this paper we focus on the factual approach to decision making principle, which mentions that the effective decisions are based on the analysis of data and information. There are many different ways of applying the factual approach to decision making principle. The nature of the organization and the specific challenges it faces will determine how to implement it.

This principle encourages an organization to do quantitative or statistical analysis based on data before making any conclusion or decision at any level within the organization. The classical quality management tools can be cause effect diagram, Pareto analysis, bar chart or statistical tool but when optimization is the goal other methods are needed.

To optimize the factual approach to decision making there are many existing methods, such as simplex-based approaches (Ignizio, 1982), modified pattern search (Clayton et al., 1982), interactive approach (Dyer, 1972), gradient based approach (Ignizio, 1982), etc. According to Baykasoğlu et al. (1999), Baykasoğlu (2006), Deb (2001) and Dhingra and Lee (1994), these classical techniques have a number of known difficulties. First, they depend on the type of objective and constraint functions (linear, non-linear, etc.) and the type of variables used in the problem modeling (integer, real, etc.). Second, they do not offer a general resolution procedure that can be handling any type of problems with different sizes of solution space and number of variables. Third, to solve a nonlinear programming problem, linearization techniques which are sensitive to the chosen starting solution, must be used. Also, the above classical approaches a well-known problem is how to guarantee the global optimization.

As a stochastic search method, a new set of independent heuristic optimization techniques (genetic algorithms, taboo search and simulated annealing) have been applied to help the Decision-Maker. These methods are more flexible, efficient and can be modified and/or adapted to specific problems requirements (Baykasoğlu et al., 1999). But they require the calibration of many parameters. However, a new method named Artificial Bees Colony (ABC) metaheuristic appears with a few numbers of parameters. In this paper, this ABC metaheuristic is used as factual approach to help decision-makers to solve a well-known combinatorial optimization problem that has captured the interest of a significant number of researchers and practitioners: the Flow-Shop Scheduling Problems with Makespan criterion (nominated as FSSPM).

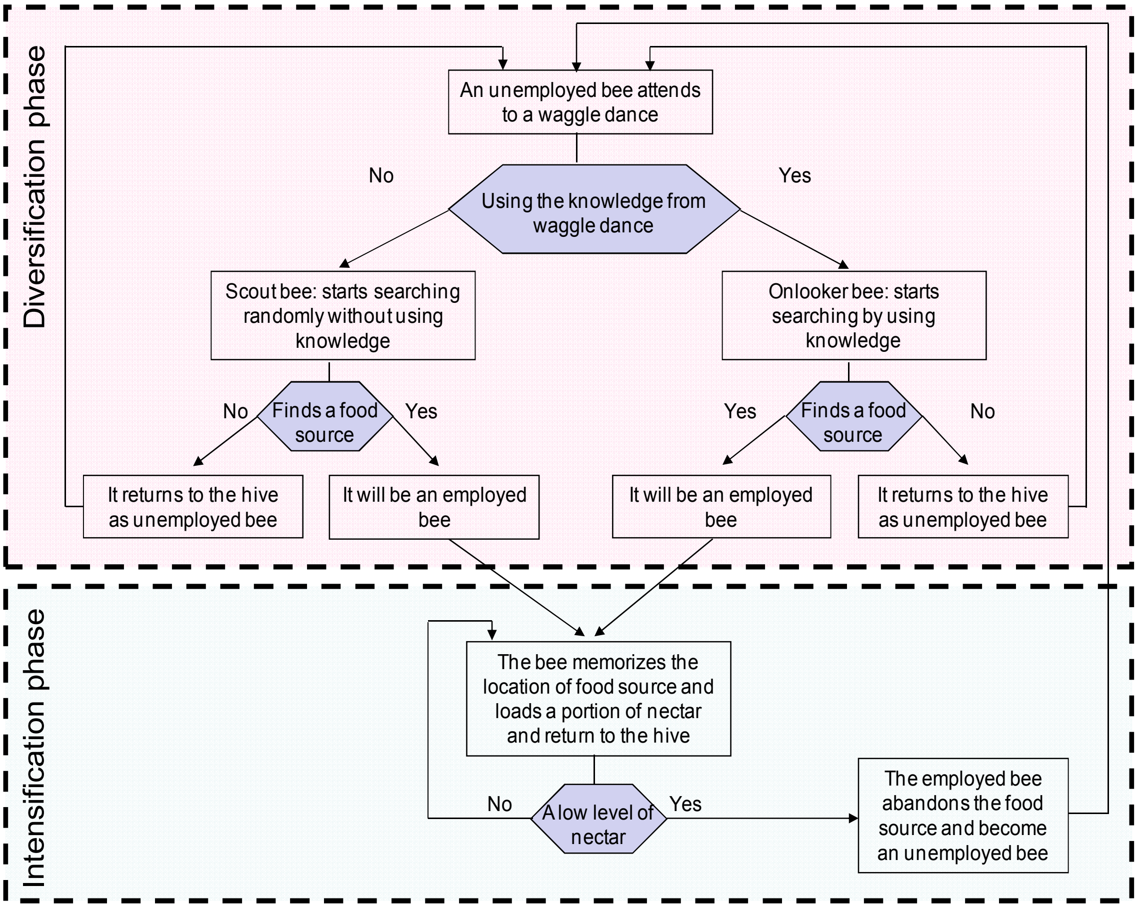
Generally, the decision makers looks for an integrated systems gathering data and model in convivial interface, for that we develop a Decision Support System (DSS). This DSS is composed of three components: in the first one, the model subsystem we develop an ABC algorithm; in the second components, the data subsystem we use a set from Or-library (described in section 3); and in the third components, the dialog subsystem a visual interactive simulation model will allow the interactive and convivial resolution using 4Dv12SQL development environment.

The remainder of the paper is organized as follows. In section 2, we recall the description of the ABC metaheuristic, as well as some of its basic properties. The Flow-Shop Scheduling Problems with Makespan criterion (FSSPM) is described in section 3. Computational results on a public benchmarks set, with up to 500 jobs and 20 machines, for the FSSPM are reported and analyzed in section 4. Section 5 concludes the paper and suggests future research directions.

2. The Artificial Bees Colony (ABC) Metaheuristic

The Artificial Bees Colony metaheuristic is an optimization algorithm proposed by (Pham et al., 2006) based on the collective intelligence of foragers bees to find food in nature. In the ABC, the bees are subdivided into employed or unemployed foragers; the main difference between them is the food source knowledge maintain.

Figure 1. The main steps of the ABC metaheuristic



The employed foragers know the distance, direction and profitability of a specific food source; they have three possibilities: 1) if the nectar in the food source is low, the employed foragers abandon the food source and become unemployed bees 2) they exploit the food source 3) they share their knowledge with unemployed bees using waggle dance. After watching this dance the unemployed bees can be either onlooker or scout bees. The onlooker bees use the knowledge given by the waggle dance and try to find a food source, whereas the scout bees do not use any knowledge and attempt to find randomly a new food source (see (Karaboga, 2005) (Karaboga et al., 2008) (Koudil et al., 2007)).

The artificial bee systems has become one of the most successful optimization algorithms due to its successful implementation in various applications for optimization problems such as image segmentation (Horng, 2015), Job Shop scheduling (Zhang et al., 2012), travelling salesman (Marinakis et al., 2011), biological simulation (Andrew et al., 2003), assignment problem (Özbakir et al., 2010), Ride-matching (Teodorović and Orco, 2008), water resource (Haddad et al., 2006), Data Mining (Benatchba et al., 2005; Banharnsakun et al., 2013), fixed point problems (Mansouri et al., 2015; Kiran and Findik, 2015), Digital image watermarking (Ali et al., 2015) and Ultrasonic Echo Problems (Zhou et al., 2015).

(Pham et al., 2006) present the main steps of the ABC algorithm

Initialize Population

Repeat

Place the employed bees on their food sources
Place the onlooker bees on the food sources depending on their nectar amounts
Send the scouts to the search area for discovering new food sources
Memorize the best food source found so far

Until requirements are met

3. Problem Formulation

The Flow-Shop Scheduling Problem with Makespan criterion problem (FSSPM) is chosen to show the performance of the proposed ABC algorithm. A set from public benchmarks with up to 500 jobs and 20 machines is used: the OR-library instances are available at (Taillard's, 1993).

Generally, the FSSPM can be noted as *n/m/Cmax* and described as a process to find a schedule of *n* jobs on *m* machines. Each job *j* on a machine *m* has a processing time p_{jm}. The machine cannot execute more than one job at the same time, and preemption of an operation is not allowed. Furthermore, each job can be processed on one machine at a time. The objective function for the FSSPM corresponds to the minimization of the Makespan (*Cmax*).

Let $C(j_n,m)$ denote the completion of job j_n on machine *m*, and let $\{j_1, j_2, \ldots, j_n\}$ denote the permutation *j* jobs, then the completion time for *n* job *m* machine flow shop is calculated as follows:
Then the *Cmax* (Makespen) is calculated by the equation 1:

$$Cmax=C(j_n,m) \quad (1)$$

Where

$C(j_1,1)=p_{j1}$

$C(j_1,2)= C(j_1,1)+ p_{12}$

$C(j_1,m)= C(j_1,m-1)+ p_{1m}$

$C(j_i,m)= max\{C(j_{i-1},m), C(j_i,m-1)\}+ p_{im}$

The FSSPM is solved by some metaheuristics methods such as the Simulated Annealing (Nearchou, 2004) (Ogbu and Smith, 1991; Osman and Potts, 1991), the Tabou Search (Ben-Daya and. Al-Fawzan, 1998), the Ant Colony (Yagmahan and Yenisey, 2008) and the Swarm Optimization algorithm (Changsheng et al., 2008).

Most of the potential SA metaheuristics for solving the FSSPM in the literature are described, developed and numerical results are presented in (Nearchou, 2004). These results are used to compare with the ABC algorithm results. In (Nearchou, 2004) four Simulated Annealing (SA) algorithms are presented: (Osman and Potts, 1989) propose a strongly SA named (Os&Po-SAA) with four schemes to generate a neighborhood, (Ogbu and Smith, 1990) (Ogbu and Smith, 1991) use a constructive heuristic for generating an initial good solution and use a novel acceptance probability function this SA algorithm is called (Og&Sm-SAA), finally (Ishibuchi et al., 1995) generate two SA named modified SAA with best move strategy (SAABM) and modified SA with first move strategy (SAABM).

4. Computational Results

The ABC algorithm is tested to solve FSSPM using the Taillard's benchmarks available from OR-library with up to 500 jobs and 20 machines: 20 * 5, 20 * 10, 20 * 20, 50 * 5, 50 * 10, 50 * 20, 100 * 5, 100 * 10, 100 * 20, 200 * 10, 200 * 20 and 500 * 20 (10 instances for each number of jobs machines). To solve the FSSPM, a solution can by represented by a permutation of the jobs. In this study, to define the solution forager bees, two randomly adjacent jobs are selected then their positions are interchanged. Furthermore, to modify the current position of an employed bee the same way is applied but without adjacent position (two randomly non adjacent jobs are selected then their positions are interchanged). In general, the usage of 10% of employed bees as the mean number of scouts averaged has been shown to be a very successful strategy (Karaboga et al., 2008) (Pham et al., 2006); also for the maximum number of unemployed forgers, it is preferred to be equal to the number of employed foragers.

Figure 2 presents the developed decision support system using 4DSQLv12 platform, this software helps the decision maker to make effective scheduling decisions based on the analysis of information: improving the factual approach to decision making principle through the ABC metaheuristic.

In Table 1, the ABC metaheuristic is compared with the algorithms presented in (Nearchou, 2004), this table proves that the ABC metaheuristic provides good solutions for all instances and using the developed DSS the decision-makers can perform well their scheduling decisions.

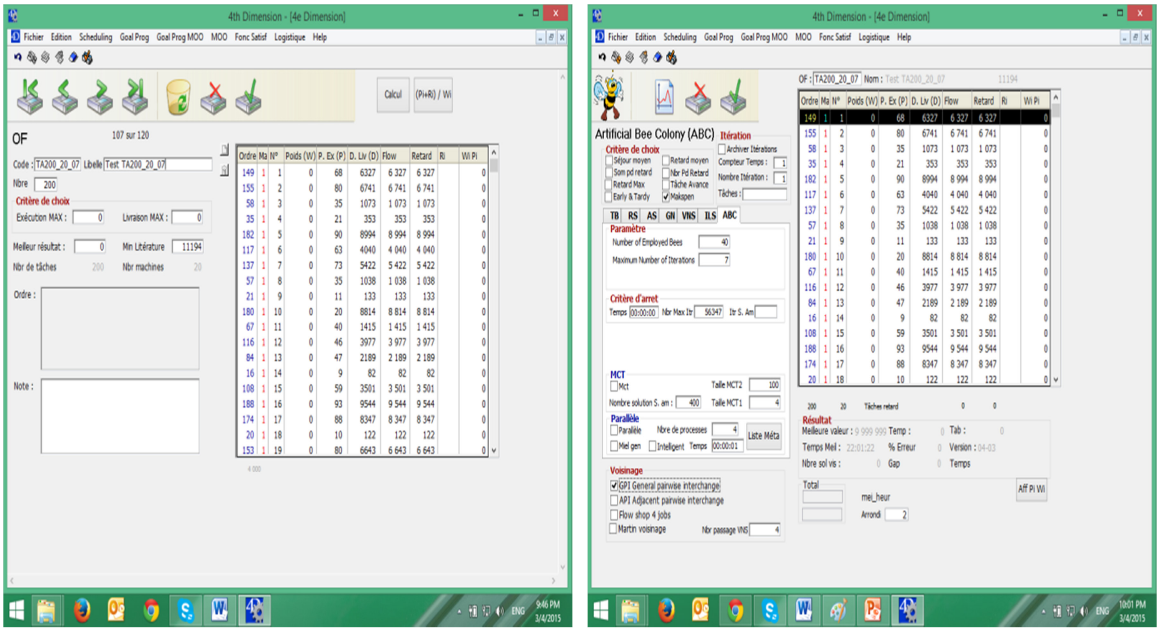


Figure 2. The developed decision support system

Table 1. Average Results for FSSPM Problems

Problems	OG&SM-SAA	OS&PO-SAA	SAABM	SAAFM	ABC
20 * 5	0.64	0.67	4.37	3.70	0.67
20 * 10	2.00	3.41	7.76	7.95	2.00
20 * 20	1.40	2.39	6.08	6.87	0.24
50 * 5	0.20	0.25	3.34	3.43	0.20
50 * 10	4.26	1.20	12.32	12.78	1.20
50 * 20	5.66	2.89	13.89	14.43	2.89
100 * 5	0.17	0.17	2.43	2.64	0.17
100 * 10	2.83	0.74	9.11	9.67	0.74
100 * 20	6.08	2.03	14.21	14.09	2.03
200 * 10	1.44	1.11	6.51	7.31	1.11
200 * 20	5.42	3.01	13.06	13.41	3.01
500 * 20	3.52	2.11	10.55	10.76	2.11
Average	2.80	1.67	8.63	8.92	1.36

The computational results for both benchmark problem sets are summarized in Table 1. The results presented in this table correspond to the best makespan over 10 runs. The results presented clearly show that in the majority of the cases investigated in this study, the average of the makespan obtained by the ABC is significantly lower than those obtained by the other techniques. These results encourage organizations to do quantitative analysis based on data before making any decision (improving the factual approach to decision making principle).

5. Conclusion

In this paper we focus on the factual approach to decision making principle, which is one of the eight basic principles in that the quality management system of the ISO 9000 series is based. The Artificial Bees Colony metaheuristic is used to improve the efficiency of this principle of factual approach to decision making. Hence, our future research aims to use the proposed Artificial Bees Colony metaheuristic to improve other basic principles for the quality management systems.

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