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Evolutionary Computation in Scheduling

A Scientometric Analysis

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1.1 Introduction

Evolutionary computation (EC) is known as a powerful tool for global optimization-inspired nature. Technically, EC is also known as a family of population-based algorithms which could be addressed as metaheuristic or stochastic optimization approaches. The term “stochastic” is used because of the nature of these algorithms, such that a primary set of potential solutions (initial population) is produced and updated, iteratively. Another generation is made by eliminating the less desired solutions stochastically. Increasing the fitness function of the algorithm resulted from evolving the population. A metaheuristic term refers to the fact that these algorithms are defined as higher-level procedures or heuristics considered to discover, produce, or choose a heuristic which is an adequately good solution for an optimization problem [1, 2]. Applications of metaheuristics can be found in the literature, largely [3–9]. Swarm intelligence algorithms are also a family of EC, based on a population of simple agents which are interacting with each other in an environment. The inspiration for these algorithms often comes from nature, while these algorithms behave stochastically and the agents possess a high level of intelligence as a colony. The most common used algorithms reported in literature are: particle swarm optimization, ant colony optimization, the Bees algorithm, and the artificial fish swarm algorithm [10–15].

Scheduling and planning problems are generally complex, large-scale, challenging issues, and involve several constraints [16–19]. To find a real solution,

most real-world problems must be formulated as discrete or mixed-variable optimization problems [16, 20]. Moreover, finding efficient and lower-cost procedures for frequent use of the system is crucially important. Although several solutions are suggested to solve the problems mentioned above, there is still a severe need for more cost-effective methods. As a result of their complexity, real-world scheduling problems are challenging to solve using derivative-based and local optimization algorithms. A possible solution to cope with this limitation is to use global optimization algorithms, such as EC techniques [21]. Lately, EC and its branches have been used to solve large, complex real-world problems which cannot be solved using classical methods [22–24]. Another critical problem is that several aspects can be considered to optimize systems simultaneously, such as time, cost, quality, risk, and efficiency. Therefore, several objectives should usually be considered for optimizing a real-world scheduling problem.

This is while there are usually conflicts between the considered objectives, such as cost-quality, cost-efficiency, and quality-cost-time. In this case, the multi-objective optimization concept offers key advantages over the traditional mathematical algorithms. In particular, evolutionary multi-objective computations (EMC) is known as a reliable way to handle these problems in the industrial domain [22, 25–27].

With the advent of computation intelligence, there is renewed interest in solving scheduling problems using evolutionary computational techniques. The spectrum of real-world optimization problems dealt with the application of EC in industry and service organizations, such as healthcare scheduling, aircraft industry, school timetabling, manufacturing systems, and transportation scheduling in the supply chain. This chapter gives a general analysis of many of the current developments in the growing field of evolutionary scheduling using scientometrics and charts.

1.2 Analysis

1.2.1 Data Collection

For this scientific literature review, we use a scientometric mapping technique to find the most common keywords used among research articles. First, we searched for the topics “evolutionary scheduling,” “metaheuristic scheduling,” and “swarm intelligence scheduling” in the SCOPUS database between 2000 and the present. We identified 1107 scientific articles. Figure 1.1 presents the distribution of papers from 2000 (articles in the area of the multi-objective vs. total number of documents).

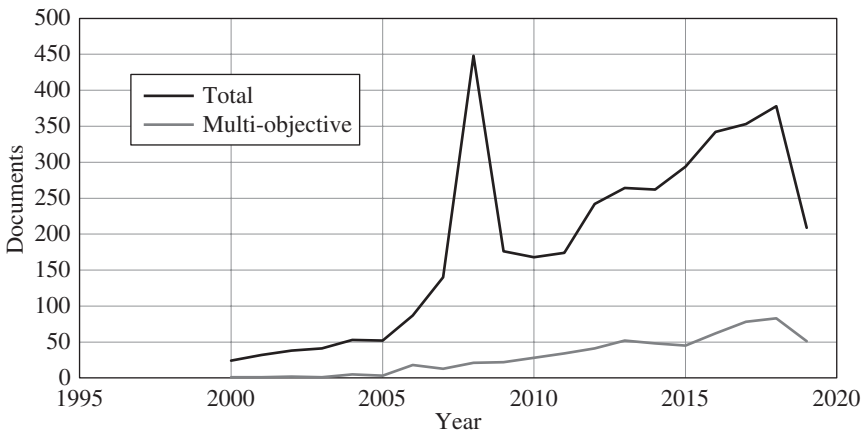


Figure 1.1 Number of documents on “Evolutionary Computation in Scheduling” (multi-objective in total).

Most of the analysis in this part has been carried out by VOSviewer, which is known as a powerful tool for scientometric analysis [28–30]).

1.3 Scientometric Analysis

1.3.1 Keywords Analysis

Figure 1.2 shows a cognitive map where the node size is comparable with a number of documents in the specified scientific discipline. Links among disciplines are presented by a line whose thickness is proportional to the extent to which two subjects are employed in one paper.

Top keywords and the number of occurrences found in the analysis are presented in Table 1.1.

1.3.2 An Analysis on Countries/Organizations

Figure 1.3 presents an organization ranking indicating the top 10 organizations which have the most contribution in the field. As is observed from Figure 1.3, the Huazhong University of Science and Technology is the most active organization in this area with 107 published documents, the Ministry of Education China and Tsinghua University are in second and third places, respectively.

Figure 1.4 illustrates the ranking of countries by number of documents. As shown, China, with almost 1100 published articles, possesses the first rank, followed by India, United States, Iran, respectively.

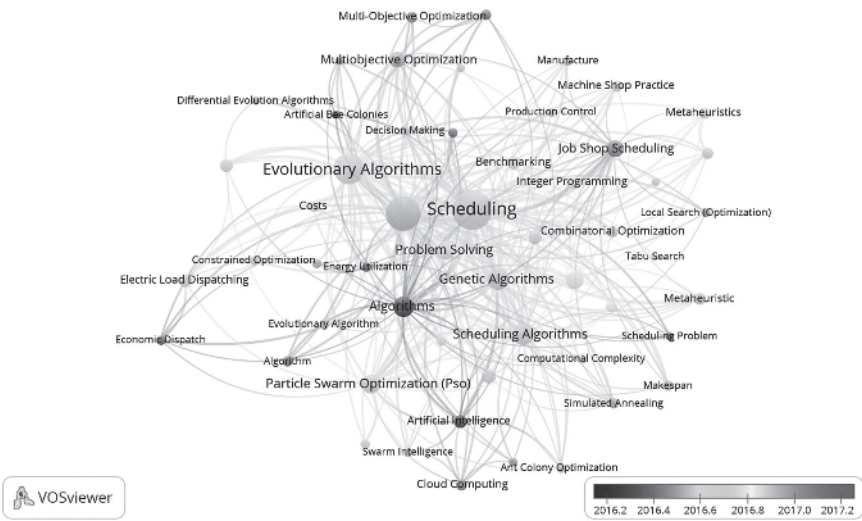


Figure 1.2 Cognitive map (keyword analysis considering co-occurrences).

Table 1.1 Top 10 keywords.

No.	Keyword	Occurrences
1	Scheduling	1185
2	Optimization	840
3	Evolutionary algorithms	698
4	Scheduling algorithms	345
5	Genetic algorithms	335
6	Algorithms	321
7	Particle swarm optimization	256
8	Problem solving	248
9	Heuristic algorithms	224
10	Job shop scheduling	208

1.3.3 Co-Author Analysis

In Figure 1.5, the analysis of co-authors and networks shows the robust and fruitful connections among collaborating scholars. The links across the networks show channels of knowledge, and networks which highlight the scientific communities engaged in research on the EC in scheduling.

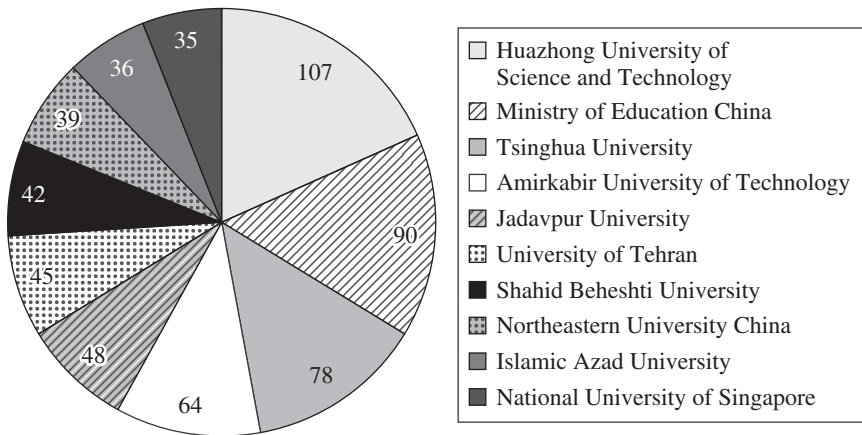


Figure 1.3 Top 10 organizations ranking by number of documents.

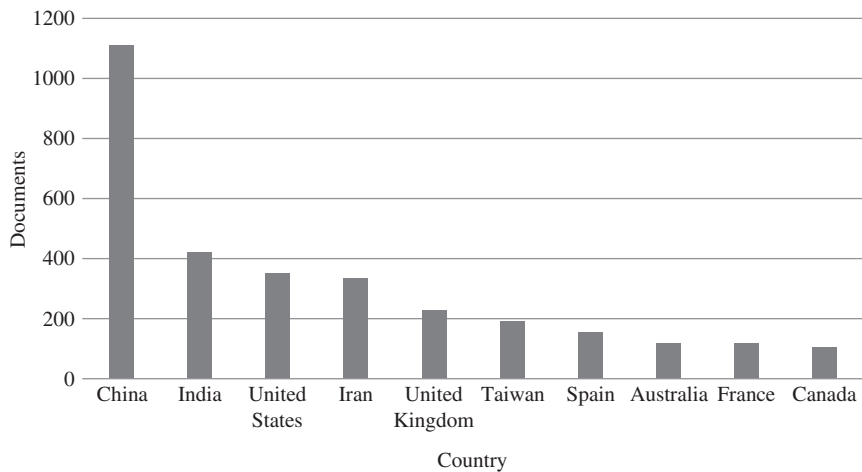


Figure 1.4 Ranking of countries by number of documents.

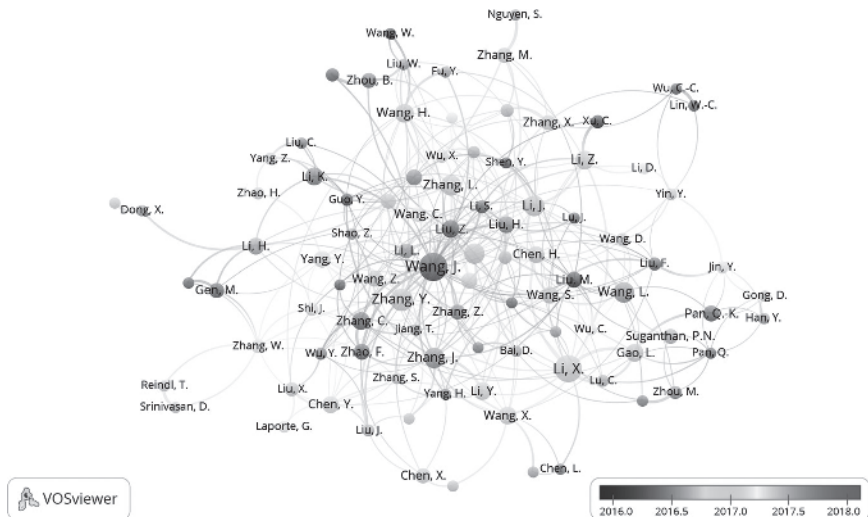


Figure 1.5 The scientific community (co-author) working on EC in scheduling.

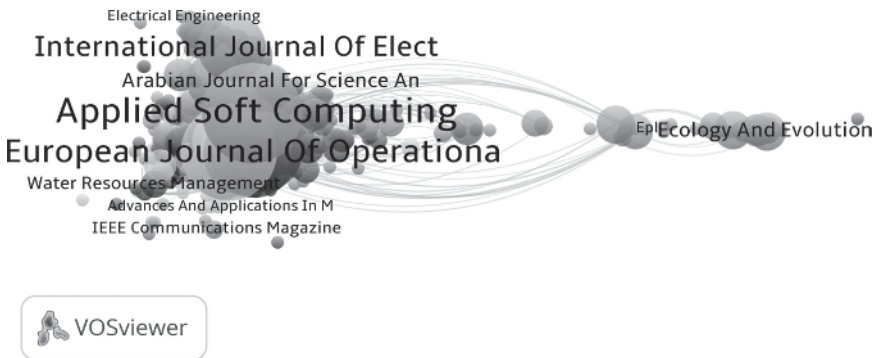


Figure 1.6 Bibliographic coupling (title).

1.3.4 Journal Network Analysis

Figures 1.6 and 1.7 show bibliographic coupling and a density map of the active sources (journals) of EC in scheduling, respectively. Figure 1.6 shows the journals aggregated by network visualization. For Figure 1.6, a bibliographic coupling analysis for sources has been used. Considering a minimum number of one document of a source, a total of 585 sources have been found. The most frequent active journals are *Applied Soft Computing*, *Computers and Industrial Engineering*, *International Journal of Advanced Manufacturing Technology*, *European Journal of Operational Research*, and *International Journal of Production Research*. The colors/shadings in Figure 1.6 represent clusters, indicating five clusters for all the items.

In Figure 1.7, the color/shading of each node in the map is related to the density of the nodes at the point. The shading ranges from high density of journals (*Applied Soft Computing*) to low density (e.g. *Neurocomputing*).

1.3.5 Co-Citation Analysis

Figure 1.8 displays the co-citation analysis of cited authors (first author only) who have a minimum of one citation for each author, resulting in 28 203 authors with strength co-citation links. In Figure 1.8, the full strength of co-citation links to other authors has been considered. The top-cited authors in the field are Kalyanmoy Deb, Eckart Zitzler, David E. Goldberg, and Edmund Kieran Burke.

1.4 Conclusion and Direction for Future Research

In this chapter, scientometric analysis of “Evolutionary Computation in Scheduling” for a time zone between 2000 and 2019 has been investigated. Keywords analysis and citation analysis fractional counting with VOSviewer software was used,



Figure 1.7 Density map.

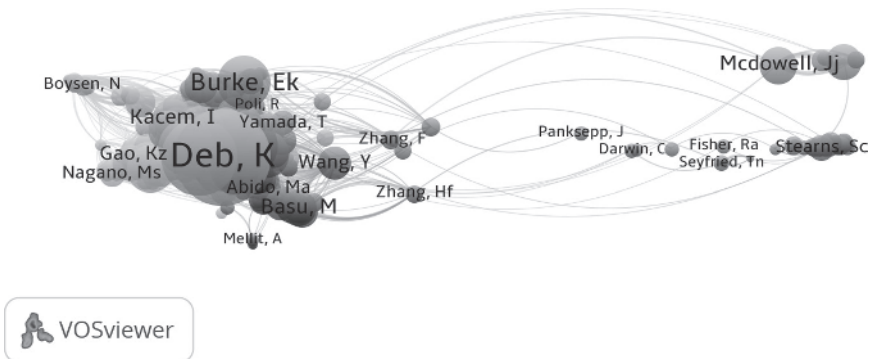


Figure 1.8 Co-citation analysis (cited authors).

and commonly used keywords were identified. The analysis includes different parts such as keyword, organization, country, bibliographic coupling, co-author, and co-citation. Keyword analysis shows that genetic algorithms and particle swarm optimization have been used frequently among other metaheuristic approaches, and job shop scheduling is the most challenging problem in the field of scheduling. China, India, United States, and Iran have the most active organizations in the research area. Moreover, co-authorship and co-citation analysis have been addressed. From a source analysis point of view, *Applied Soft Computing*,

Expert System with Application, *European Journal of Operational Research*, and *Annals of Operations Research* have been found as well-known active journals in the field.

As a future study, it is recommended to do other analyses with more detail, such as co-citation analysis on cited references and cited sources and/or bibliographic coupling analysis on authors. The analysis also shows how interdisciplinary works have been focused recently; more research in this area is recommended. There are also some other gaps which need to be focused on: robustness is one of these urgent needs, where practitioners should focus more on solving real problems. Scalability is another issue in the field; applicability of EC algorithms in the case of big data is an important matter for practical problems. Comparative works which try to compare evolutionary algorithms and other methods could be also a promising area for more research in the future, especially when tackling these problems in different sources of benchmark data.

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