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Invited Review

Multi-objective meta-heuristics: An overview of the current state-of-the-art

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Abstract

This paper gives an overview of meta-heuristics methods utilized within the paradigm of multi-objective programming. This is an area of research that has undergone substantial expansion and development in the past decade. A literature review for this period is presented and analyzed. Analysis of the types of multi-objective techniques and meta-heuristics is undertaken and reasons for their use hypothesized. The strengths and weaknesses of meta-heuristic methods as applied to multi-objective programmes are discussed. Finally, a summary is given together with suggestions for future research. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Multi-objective programming; Compromise programming; Goal programming; Meta-heuristics; Genetic algorithms; Simulated annealing; Tabu search

1. Introduction

Many situations and problems faced by decision-makers in the real-world are recognized to be multi-objective. That is, there does not just exist a single criterion by which the success of a particular solution can be measured. Rather, there exist multiple criteria to be satisfied or achieved. Frequently, the objectives to be achieved over these criteria conflict with each other. In this case, there does not exist a single ideal solution which simultaneously satisfies the decision-maker across all criteria. Therefore, a compromise solution must be sought in accordance with the preferences of the decision-maker. The mathematical process of seeking such a solution is known as multi-objective programming. Earlier generations of operational research techniques dealt with this problem by assigning one criterion to be optimized and the other criteria were given minimal levels below which the solution is deemed infeasible. Linear programming falls into this category.

However, recent decades have seen an increase in the awareness of multiple objectives and the design of multi-objective programming techniques to handle such situations. The most popular include methods for the generation of the efficient

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frontier [9] (from henceforth referred to as classical MOP), goal programming [1,3,6], and compromise programming [11,12]. These techniques have a common mathematical root but differing underlying philosophies. A comparison between these methods is given by Romero et al. [7].

Standard solution techniques for these models have been available for some time. These are mostly simplex-method based and are described by Steuer [9] and Ignizio and Cavalier [3]. However, these methods are based around the standard linear and integer cases. In real-world situations one of a number of complicating factors may occur which makes the resulting model hard to solve. Types of complicating factors include large numbers of integer or binary variables, non-linearities, stochasticity, non-standard underlying utility functions, and logical or non-standard constraints and feasibility conditions. These type of complicating factors are particularly prevalent in the practical disciplines such as engineering and medicine.

In the past such complicating factors had limited the use of both single-objective and multi-objective models for the modelling of such situations. However in the last decade two advances have made better modelling of such situations possible. The first advance is a large increase in computing power and hence speed of solution that has been made available to the modeller. The second is the development of more appropriate algorithms for tackling such models. The principle advance here has been in the area of meta-heuristics. A heuristic is defined by Reeves [5] as a technique which seeks or finds good solutions to a difficult model. A meta-heuristic goes beyond this to draw on ideas and concepts from another discipline to help solve the artificial system being modelled. The most popular meta-heuristics include genetic algorithms [2], which emulate the way species breed and adapt in the field of genetics; simulated annealing, which emulates the way in which a material cools down to its steady state in the field of physics; and tabu search, which draws on the social concept of 'taboo' in order to provide an effective search technique which avoids local optima.

The remainder of this paper is dedicated to exploring the way in which multi-objective meta-heuristics have developed in the past decade and of detailing the current state-of-the-art in the area. Section 2 presents a literature review of the period and discusses trends and applications by referring to a series of figures. Section 3 details strengths and weaknesses of meta-heuristics and give suggestions as to their successful use. Finally Section 4 presents a summary.

2. Literature review and analysis

The review of the literature in this paper consists of 115 articles concerned with the theory and application of multi-objective meta-heuristics. These papers are listed in the bibliography ([13–127]) and are drawn from the period 1991–1999. The articles in the literature review have been drawn from refereed journal articles from across a broad range of disciplines. Books and conferences proceedings have generally not been included, although the tendency is to be inclusive when dealing with borderline cases. There is not a significant amount of application before 1991, although there exists some important theoretical work which is discussed in Section 3 and included in the bibliography [1–12].

Fig. 1 demonstrates the rise in popularity of multi-objective meta-heuristics in the period mentioned. Several factors influenced this increase. Firstly, there exists an increase in computing power that allows these techniques to be more fully utilized. Secondly there is the transferral effect of advances in meta-heuristic methods and their application to single-objective models that is subsequently extended into multi-objective models. Thirdly, a growing awareness during the

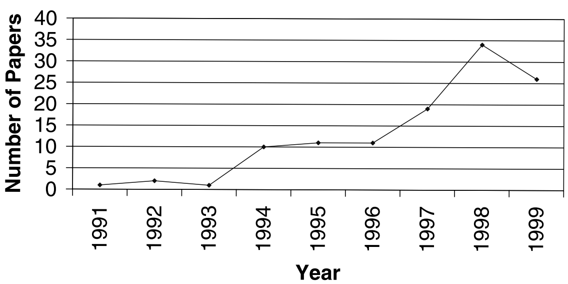

Fig. 1. Article frequency in the period 1991–1999.

decade of the existence and importance of multiple objectives in various disciplines.

Fig. 2 gives the application areas of the articles. Note that the theoretical papers account for 24 of the 115 articles, or 20.9%. This is a healthy ratio as it indicates that these techniques have a lot of real-world usage, rather that just theoretical value. But the application nevertheless does have the correct theoretical foundation.

Another observation arising from Fig. 2 is the number of articles concerning the practical disciplines of engineering and medicine as opposed to the business and managerial disciplines of conventional OR and socio-economic planning. This is significantly higher than in, say, a standard multiple criteria decision making (MCDM) or MOP literature review. This can be explained by the existence of the complicating factors described in Section 1 that make multi-objective meta-heuristic solution attractive. Thus multi-objective meta-heuristics can be said to have brought multiple objective programming methods effectively into these disciplines.

Fig. 3 clearly demonstrates the prevalence of the classical multi-objective programming techniques in application of MOP (90%). One reason for this is some important theoretical algorithms developed in the 1980s and early 1990s for generation and approximation of the efficient set by genetic algorithm methods. These include the vector evaluated genetic algorithm of Schaffer [8], the non-dominated sorting algorithm (NDSA) of Srinivas and Deb [10] and the multi-objective genetic algorithm (MOGA) method of Fonesca and Fleming [53]. The underlying reason for the success of such approaches is the fact that genetic algorithms can naturally produce multiple solutions, and therefore provide an ideal tool for generating a representation of the many solutions that comprise the efficient set. This means that more advances have been made in the area of classical MOP meta-heuristics than of techniques such as goal programming (accounting for 7% of the articles) which are based around a single solution. Meta-heuristics tend to be used in goal programming when there exist sufficient complicating factors so as to make solution by conventional optimization technique either inefficient or impossible. A comparison between conventional methods and genetic algorithms for a class of goal programming models is given by Mirrazavi, Jones, and Tamiz [4]. There exists potential for the development of meta-heuristic methods in the areas of compromise programming and interactive methods, both of which require multiple solution generation but account for only 1% and 2% of the articles, respectively.

Fig. 4 shows that 70% of the articles utilize genetic algorithms as the primary meta-heuristic, 24% simulated annealing, and 6% tabu search. Although this gives a slightly weak representation of tabu search as it is frequently used in conjunction with either genetic algorithms or simulated annealing as a secondary meta-heuristic refinement in order to strengthen the avoidance of convergence at local optima. The overall spread reflects

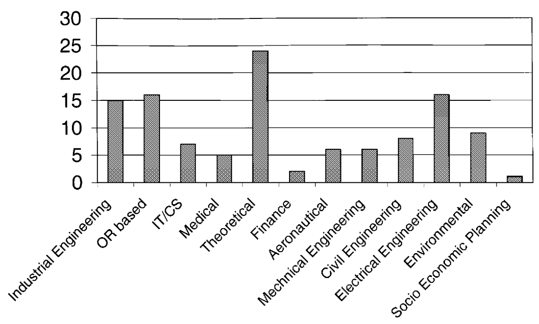

Fig. 2. Breakdown of articles by application area.

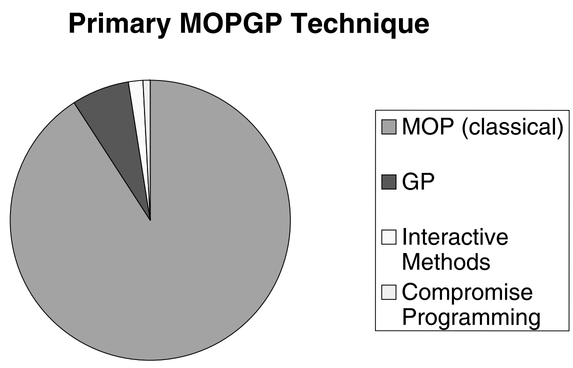

Fig. 3. Breakdown of articles by primary multi-objective technique.

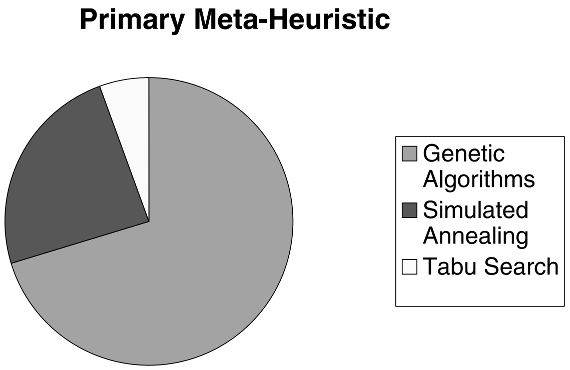

Fig. 4. Breakdown of articles by primary meta-heuristic method.

the popularity and flexibility of genetic algorithms as a meta-heuristic methods, although many authors appear to be using simulated annealing when they feel it is most appropriate. There is no sign in the literature reviewed of the newer meta-heuristic techniques such as GRASP or ant-colony optimization being applied in the multi-objective case. This is an area for future research.

3. Strengths and weaknesses

In order to see where meta-heuristics can be successfully applied within the multi-objective paradigm, it is first necessary to understand their natural strengths and weaknesses, and how these translate into multi-objective optimization terms.

The first point to note is that most meta-heuristics are naturally discrete, as opposed to conventional models which are mostly naturally continuous. This means that meta-heuristic models can handle models with integer variables, discrete variables, and/or logical (binary or zero-one) variables well. Whereas continuous variables have to be discretized by approximation before the meta-heuristic is applied. The greater the degree of accuracy demanded at this stage, the larger representation is needed, and the more computational effort is required.

Another advantage of meta-heuristic methods is their flexibility. The range of models capable of being solved by meta-heuristics is far greater than that by conventional methods. In particular, models with complicating factors (as described in Section 1) can be more easily handled. Also, problem-specific knowledge can be more easily integrated into the solution process than in a conventional method. Non-standard goals, constraints, objectives and conditions can be more easily incorporated. This flexibility has broadened the range of problems to which multi-objective methods are applied, particularly in the fields where the above conditions exist, i.e., most engineering disciplines and medicine.

There are a number of disadvantages to using meta-heuristics as opposed to conventional methods. The primary observation is that meta-heuristic methods are not function optimizers. That is, their purpose is to seek and find good solutions to the problem, rather than a guaranteed optimal solution. Therefore, if the model is sufficiently simple as to allow conventional methods to be able to produce an optimal solution, there seems little point in using a meta-heuristic method. However, the articles reviewed in this survey deal with complex real-world systems for which there is no conventional method that is guaranteed to find the optimal – this is the type of problem where multi-objective meta-heuristics should be considered. Other disadvantages include the fact that there exist a larger number of parameters to be set by the modeller in meta-heuristics than in conventional methods. The solution is sensitive to these parameters in many cases and hence a number of executions of the meta-heuristic with different parameter sets are sometimes needed before a good solution is produced. This means meta-heuristics make a poor 'black box' and are more difficult to apply when only a single run of the meta-heuristic is allowed due to time or other pressures. Finally, meta-heuristic methods are known to struggle with certain tightly constrained models, although advanced constraint handling techniques and methods are now available [2].

4. Summary and scope for future research

This overview has shown that there has been a substantial growth of meta-heuristic methods within the paradigm of multi-objective programming in the past decade. This has had the positive effect of expanding the scope of multi-objective programming, particularly in fields with models that are naturally difficult to solve models, such as the engineering disciplines.

The discussion in this overview has also shown areas for future research and development in this growing field. In particular there appears to be scope for the development of meta-heuristic methods for other multi-objective methods, such as compromise programming and interactive methods. In addition, some of the newer meta-heuristics, such as ant-colony optimization and GRASP have yet to be applied to multi-objective programming models. Also, there exists the need to develop analysis techniques for the new meta-heuristic methods that already exist for the conventional simplex-based methods. Such analysis tools include sensitivity analysis, Pareto efficiency checking and restoration for goal programming, and redundancy checking for lexicographic models.

Overall, meta-heuristics have been proved to be useful tools that have their own set of advantages and disadvantages. It is important to note that they are not a global panacea for every multi-objective programming problem. In some cases it is possible and more appropriate to use conventional methods. Mirrazavi et al. [4] give an example of one such class of multi-objective problems. However, most of the articles in the literature review fall into categories of models not solvable or not appropriate for solution by conventional methods. For these types of models it is hypothesized that the next decade will see a growth in power and accuracy of multi-objective meta-heuristic solution and analysis tools to allow improved solutions to be generated and a more accurate representation of decision-makers, preferences to be given.

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