F1.2 Management applications and other classical optimization problems

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Abstract

In this section an evaluation of the current situation regarding evolutionary algorithms (EAs) in management applications and classical optimization problems is attempted. References are divided into three categories: practical applications in management, application-oriented research in management, and standard optimization problems with relevance beyond the domain of management. Some general observations on the competitiveness of EAs, as compared to other optimization techniques, are also given. Few systematical and large-scale comparisons have appeared in the literature so far, and it is fair to state that a thorough evaluation of the potential of EAs in most of the classical optimization problems is still ahead of us. This is partly due to the lack of suitable benchmark problems, representative for distinct and neatly specified problem classes. Besides, theoretical results also shed a rather critical light on the objectives and current practice of empirical comparisons.

F1.2.1 Introduction

In recent years, new heuristic techniques, some of them inspired by nature, have emerged which have proven successful in solving very diverse hard optimization problems. Evolutionary algorithms (EAs), tabu search (TS), and simulated annealing (SA) are probably the best known classes of these modern heuristics. They share common characteristics. For instance, they tolerate deteriorations of the attained solution quality during the search process to overcome local suboptima in complex search spaces.

In this section, EAs are viewed as stochastic heuristics, applicable to a large variety of complex optimization problems. They are based on the mechanisms of natural evolution, imitating the phenomena of heredity, variation, and selection on an abstract level. The mainstream types of EA are:

- genetic algorithms (GAs)
- genetic programming (GP)
- evolution strategies (ESs)
- evolutionary programming (EP).


In an attempt to structure one important area of applied EA research, this paper gives an overview of EA in management applications, also covering other classical optimization problems with relevance beyond the domain of management. More than 850 references to current as well as finished research projects and practical applications are classified in Appendix B. (The references in this text are collected in a separate reference list, located before the appendices.) Although much effort has been devoted to

† This section is an updated and extended version of Nissen (1993, 1995).
collecting and evaluating as many references as possible, the list cannot be complete. Furthermore, it must be assumed that many applications remain unpublished for reasons of confidentiality. Hence, the results reported in section F1.2.2 might be unintentionally biased. However, it is hoped that others will find the classification of applications and extensive reference list helpful in their own research. Moreover, some general observations on the competitiveness of evolutionary approaches as compared to other paradigms are included in section F1.2.3.

**F1.2.2 An overview of evolutionary algorithm applications in management science and other classical optimization problems**

**F1.2.2.1 Some technical remarks**

This overview is mainly based on an evaluation of the literature and information posted to the relevant e-mail discussion lists *Genetic Algorithms Digest* (ga-list-request@aic.nrl.navy.mil), *Evolutionary Programming Digest* (ep-list-request@magenta.me.fau.edu), *Genetic Programming List* (genetic-programming-request@cs.stanford.edu), the EMSS list (dduane@gmu.edu) on evolutionary models in the social sciences, and two other specialized lists on timetabling (ttp-request@cs.nott.ac.uk) and scheduling (gsched-owner@acse.sheffield.ac.uk) with EAs. Additional information was gathered by private communication with fellow researchers, consultants, software developers, and users of EAs in business.

Sometimes it was rather difficult to decide, on the basis of the literature reviewed, whether papers actually discussed a practical application in business (section F1.2.2.2) or ‘just’ application-oriented research (section F1.2.2.3). When only test problems were discussed without reference to a practical project then no immediate practical background was assumed. This also applies to projects using historical real data. Application-oriented research in management, and other classical optimization problems (section F1.2.2.4) are two evaluations that refer to projects not linked to practical applications in business. The section on other classical optimization problems concerns management as well as different (e.g. technical) domains. A well-known example for such a general standard problem with applicability in different domains is the *traveling salesman problem* (TSP).

Multiple publications on the same project count as one application, but all evaluated references are given in the tables of Appendix A and are listed in the extensive bibliography of Appendix B. The year of earliest presentation of an application, as given in the tables, generally refers to the earliest source found, which might be personal communication preceding a publication. In some cases, authors (Koza, Michalewicz) have included all previously published material in easily accessible books or long papers. Here, only the overall references are cited in the reference list.

For the majority of cited references the original papers were available for investigation. In some cases, however, secondary literature had to be used, because it was impossible or too difficult to obtain the original sources. Some additional references may be found in the bibliographies compiled by Alander (1996a, b, c, d) and available through the Internet (ftp://ftp.uwasa.fi.directory.cs/report94-1).

In this section, and particularly in the tables, a unified view on the field of EAs is taken. Even though the GA community is by far the largest, it is probably true that any of the EA mainstream types could be applied to any of the fields discussed here. Generally, a good optimization technique will account for the properties and biases of the problem investigated. The most reasonable solution representation, search operators and selection scheme will, therefore, depend on the problem. In this context, the entire field of EAs may be thought of as some form of toolbox. Whether the result of EA design for a particular problem on the basis of such a toolbox is called a GA, GP, EP or an ES is not really important, and might even be hard to decide. However, in the following overview sections the frequency of certain EA mainstream types will be mentioned for reasons of completeness.

**F1.2.2.2 Practical applications in management**

An overview of practical management applications is given in table F1.2.1. To date the quantity and diversity of applications is still moderate if one compares with the huge variety of optimization problems faced in management. Besides, many systems referred to in table F1.2.1 must be considered prototypes. Although the information is hard to extract from the given data, the number of running systems actually applied routinely in daily practice is likely to be rather small.

Combinatorial optimization with a focus on scheduling is most frequent. The majority of applications appear in an industrial setting with emphasis on production (figure F1.2.1). This is not surprising, since
production can be viewed as one large and complex optimization task that determines a company’s competitive strength and success in business. Other business functions such as strategic planning, inventory, and marketing have not received much attention from the EA community so far, although some pioneering publications (see also table F1.2.2) have demonstrated the relevance of EAs to these fields.

The financial services sector is usually progressive in its electronic data processing applications, but publications in the scientific press are rather scarce. A focus on credit control and identification of good investment strategies is visible, though. The actual number of EA applications in this sector is likely to be much higher than the figures lead us to believe. This might also hold for management applications in the military sector. In these unpublished applications GAs are the most likely type of EA employed, since their research community is by far the largest.

The energy sector is another prevailing area of application. ESs are quite frequent here, because this class of EAs originated in the engineering field and has traditionally been strong in technical applications. GAs are most frequently applied in practice. Interest in the other EA types is growing, however, so that a rise in the number of their respective applications can be expected in the near future. ESs and EP already cover a range of management-related applications. GP is a very recent technique that has attracted attention mainly from practitioners in the financial sector, while GP researchers are still working to reach the level of practical applicability in other domains.

Some hybrid systems integrating EAs with artificial neural networks, fuzzy set theory, and rule-based systems are documented. Since they are expensive to develop and may yield considerable strategic advantage over competitors, it can be assumed that much work in hybrid systems is kept secret and does not appear in the figures. This also holds for applications developed by commercial EA suppliers, sometimes with the aid of professional and semiprofessional EA tools. The quality of the data suffers from the fact that many authors are not allowed to publish their applications for reasons of confidentiality.

If one considers the publication dates of practical EA applications (figure F1.2.2), a sharp rise in publications since the late 1980s is obvious. This movement can almost solely be attributed to an increased interest in GAs where the number of researchers has risen dramatically. To infer that GAs
Management applications and other classical optimization problems

Figure F1.2.2. Practical applications ordered by earliest year of presentation as of July 1996.

are superior to other EA mainstream types can not be justified by these figures, though. It is rather the good 'infrastructure' of the GA community that fuels this trend: regular GA conferences since 1985, the availability of introductory textbooks, (semi-) professional GA tools, a well-organized and widely distributed newslsit (GA Digest), and cumulative effects following successful pilot applications.

All in all, it seems fair to say that we have not seen the big breakthrough of EAs in management practice, yet. Interest in these new techniques, however, has risen considerably since 1990 and will lead to a further increase in practical applications in the near future.

F1.2.2.3 Application-oriented research in management science

This evaluation (table F1.2.2) focuses on research in management science that is not linked to any practical project in business. There is a strong focus on GAs, even more than in practical applications. The overall picture with respect to major fields of interest and EA types used is similar to that of the previous section. However, the quantity and diversity of projects is larger than in practical applications. Research interest in production planning and financial services is particularly high.

Notable is the strong bias of research for jobshop and flowshop scheduling. Production planning is an important problem in practice, of course. However, the standard test problems used by many authors frequently lack many of the practical constraints faced in production (see also section F1.2.3). Research on standard operations research problems such as jobshop scheduling sometimes seems to be some sort of tournament where the practical relevance of the approach comes second to minimal improvements of some published benchmark results on simplifying test problems.

F1.2.2.4 Other classical optimization problems

Table F1.2.3 lists EA applications on classical optimization problems with relevance to not only management science but other domains as well. Many of them refer to randomly generated data or benchmark problems given in the literature. The interested reader will find some applications from evolutionary economics under the heading iterated games.

Besides GAs (most frequent) and ESs, some applications of EP, GP and learning classifier systems are found in the area of game theory, as well as in some combinatorial problems such as the TSP. The TSP is a particularly well-studied problem that has led to the creation of a number of specialized recombination operators for GAs. The potential of GAs for the field of combinatorial optimization is generally considered to be high, but there has been some scientific dispute on this theme (see GA Digest 7 (1993), issue 6 and subsequent issues).
F1.2.3 Some general observations on the competitiveness of evolutionary algorithms

F1.2.3.1 Mixed results

Given the limited space available, it is impossible to discuss here in detail the implementations, advantages and disadvantages of EAs in particular optimization problems. However, some rather general observations will be presented that follow from the published literature, personal experience, and discussions of the author with developers and users of EAs.

Only a few systematic and large-scale empirical comparisons between EAs and other solution techniques appear in the literature. The most recent and quite extensive investigation was carried out by Baluja (1995). He compares seven iterative and evolution-based optimization techniques on 27 static optimization problems. The problem set includes jobshop scheduling, TSP, knapsack, binpacking, neural network weight optimization, and standard numerical function optimization tasks. Such problems are frequently investigated in the EA literature. Two GAs, three variants of multiple-restart stochastic iterated hillclimbing, and two versions of population-based incremental learning are compared in terms of speed and the best solution found in a given number of trials. The experiments indicate that algorithms simpler than standard GAs can perform competitively on both small and large problem instances.

Other empirical studies support these results. For instance, the investigations by Park and Carter (1995), Park (1995), Goffe et al (1994), Ingber and Rosen (1992), and Nissen (Section G9.10 of this handbook) all show no advantage or even disfavor EAs over SA and the related threshold accepting heuristic on classical optimization problems such as the Max-Clique, Max-Sat, and quadratic assignment problems.

In contrast, many examples can be found in the literature where evolutionary approaches compete successfully with the best solution techniques available so far. We only mention the works of Falkenauer on binpacking and grouping problems (Falkenauer and Delchambre 1992, Falkenauer 1994, 1995), Khuri et al on vertex cover and multiple-knapsack problems (Khuri et al 1994, Khuri and Bäck 1994), Lienig and Thulasiraman on routing tasks (Lienig and Thulasiraman 1994), Fleurent and Ferland on the quadratic assignment problem (Fleurent and Ferland 1994), and Parada Daza et al on the two-dimensional guillotine cutting problem (Parada Daza et al 1995). Moreover, the author knows of further practical applications of EAs in business where excellent results were produced in highly constrained complex search spaces.

These rather mixed results pose a problem for practitioners in search of the most promising optimization technique for a given hard problem. On the one hand, the current situation reflects the enormous difficulties associated with empirical crossparadigm comparisons. These difficulties concern benchmark problems and benchmark results. On the other hand, theoretical evidence suggests that the quest for a universally superior optimization technique is ill directed. The following sections take up these issues in some more depth.

F1.2.3.2 Benchmark problems

The first requirement for a systematic empirical comparison of different optimization methods is a representative set of instances for the investigated problem class. This in turn demands the neat specification and description of the relevant characteristics of this class. As Berens (1991) correctly points out, the success of an optimization method may change drastically when parameters of the given problem class are varied. Examples of such parameters are the problem size as well as structural aspects (such as symmetry and variance of entries in data matrices).

Moreover, real-world applications often involve multiple goals, noisy or time-varying objective functions, ill-structured data, and complex constraints that are usually not covered by standard test problems available today. Thus, if one does not want to be restricted to trivial toy problems many details can be necessary to correctly specify a problem class, and a sizeable number of problem instances might be required to cover the class representatively. As an example, Brandeau and Chiu (1989) have identified 33 characteristics to specify location problems. The complexity of creating meaningful benchmark problems is further raised by including aspects such as deception, epistasis, and related characteristics commonly used to establish the EA hardness of a problem.

At present, we are far from having suitable problem class descriptions and publicly available representative benchmark problems on a broad scale. The necessity to collect or generate them is generally acknowledged, though. Beasley’s OR library of test problems (1990), available through the Internet from Imperial College in London, is a step in the right direction (http://mscmga.ms.ic.ac.uk/info.html). However,
it should be noted that it is extremely difficult to validate the suitability of any finite set of benchmark problems.

**F1.2.3.3 Benchmark results**

For a meaningful empirical comparison of competing optimization methods comparable statistical data are required. This is far from trivial. Several decisions must be taken in setting up the empirical test.

*Choosing the right competitors.* The comparison will have only limited significance unless we compare our approach with the strongest competitors available. It can require considerable effort to establish what paradigms should be compared. One reason is that certain very promising new heuristic techniques such as threshold accepting (Dueck and Scheuer 1990, Nissen and Paul 1995) are not widely known, yet. Others, such as tabu search and neural network approaches, have only been tested on a limited subset of classical optimization tasks, although they are potentially powerful in other problem classes as well.

*Use results from the literature, or implement all compared paradigms?* Implementing each optimization technique and performing experiments on the problem data is a very laborious task. Moreover, precise descriptions of every important detail of all compared paradigms are required. It is frequently difficult to obtain these precise descriptions from the literature. Even worse, as Koza points out in a recent posting to the *GP List*, one usually cannot avoid an unintentional bias in favor of the approach one is particularly familiar with.

However, suitable statistical data cannot in most cases be extracted from the literature. Authors use different measures to characterize algorithmic performance, such as the best solution found, mean performance, and variance of results. The number of runs to obtain statistical data for a given optimization method can vary between 1 and 100 in the literature. Moreover, differing hardware and software makes efficiency comparisons between own data and published results difficult.

Asking authors for the code that was used in generating published benchmark results can also lead to many difficulties related to program documentation, programming style, or hardware and software requirements.

*Algorithmic design and parameter settings.* There are numerous published variants of EAs, particularly concerning GAs. GAs were originally not developed for function optimization (De Jong 1993). However, much effort has been devoted to adapting them to optimization tasks, especially in terms of representation and search operators. Additional algorithmic parameters such as population size and population structure, crossover rate, and selection mechanism result in a considerable design flexibility for the developer. The same applies, albeit to a lesser extent, to other optimization methods one wishes to investigate.

This freedom in designing the optimization techniques and the difficulty of determining adequate strategy parameter settings adds further complexity to crossparadigm comparisons. It is impossible to test every design option. Additionally, there are different opinions as to whether a fair empirical comparison should focus on the generality of a method over many problem classes, or the power in one specific area of application. Generally, a tradeoff between the power and the generality of a solution technique will be observed (Newell 1969). Baluja (1995), for instance, who disfavors GAs, concentrates on generality. Successful evolutionary approaches, on the other hand, frequently apply a highly problem-dependent representation or decoding scheme and search operators, or they use hybrid approaches that combine EAs with other techniques (see, for example, the works of Davis (1991), Mühlenbein (1989), Liepins and Potter (1991), Falkenauer (1995), and Fleurent and Ferland (1994, 1995)). This leads to the next difficult decision.

*Quality indicators for comparisons of optimization techniques.* Besides the characteristics of power and generality there are many other aspects of an optimization technique that could be used to assess its quality. Examples include efficiency and ease of implementation. Matters are further complicated in that even the definition and measurement of these quality indicators is not universally agreed upon.

*Conduct of the empirical comparison.* The general setup of the experiments is crucial for the validity of results. Important decisions include the method of initialization, the termination criterion, and the number of runs on each problem instance.
Besides these difficulties in conducting meaningful empirical comparisons, theoretical results also suggest that it is hard to come to general conclusions about advantages and disadvantages of evolutionary optimization.

F1.2.3.4 Implications of the no-free-lunch theorem

Recently, Wolpert and Macready (1995) published a theorem that basically states the following (the no-free-lunch, NFL, theorem): all algorithms that search for an extremum of a cost function perform exactly the same, when averaged over all possible cost functions. This result is not specific to EAs but also concerns competing optimization methods.

Some very practical consequences follow from this theorem. They are not really new to optimization practitioners. However, the NFL theorem provides some useful theoretical background.

- The quest for an optimization technique that is generally superior is ill directed, as long as the area of application is not narrowly and precisely defined.
- Good performance of an optimization technique in one area of application will not guarantee equally good results in a different problem area.
- It is necessary to account for the particular biases and properties of the given cost function in the design of a successful algorithm for this application. In other words, one should start by analyzing the problem before thinking about the proper solution technique. Empirical comparisons, however, frequently proceed in the opposite direction, taking some broadly applicable optimization techniques and then looking for suitable test problems.

It is hard to come to general conclusions on advantages and disadvantages of EAs, given the NFL theorem and the difficult empirical situation. The statements in the following section should be taken as the author’s subjective view.

F1.2.3.5 Some advantages and disadvantages of evolutionary algorithms

To start with an advantage, it is not difficult to explain the basic idea of EAs to somebody completely new to the field. This is of great importance in terms of practical acceptance of the evolutionary approach.

An advantage and disadvantage at the same time is the design flexibility of EAs. It allows for adaptation to the problem under study, and the breadth of known EA applications gives testimony to this. EAs have in a relatively short time demonstrated their usefulness on an impressive variety of difficult optimization problems, including time-varying and stochastic environments. Algorithmic design of an EA can be achieved in a stepwise, prototyping-like manner. It is easy to produce a first working implementation that can then be improved upon, including domain-specific knowledge and using the ‘EA toolbox’ mentioned before. This adaptation of the method, however, requires empirical testing of design options and a sound methodical knowledge. In this sense, the many strategy parameters of today’s EAs are clearly a disadvantage, as compared to simpler competing optimization methods.

The basic EA types are broadly applicable and, in contrast to many of the more traditional optimization techniques, make only weak assumptions about the domain under study. They can be applied even when the insight into the problem domain is low. In fact, EAs can be positioned along a continuum from weak, broadly applicable methods to strong, highly specialized methods. (Compare also Michalewicz’s hierarchy of evolution programs (Michalewicz 1996).) Moreover, there are a variety of ways of integrating and hybridizing EAs with other existing methods, as evidenced by numerous publications. These advantages will, however, in general also hold for similar modern heuristics, such as SA or tabu search, even though they might currently lag behind in terms of total research effort spent.

With these competitors EAs also share some disadvantages. First, EAs can generally offer no guarantee of identifying a global optimum in limited time. They are of heuristic character. However, in practical applications it is often not necessary to find a global optimum, but a good solution will suffice. Unfortunately, it is difficult to predict the solution quality attainable with EAs on arbitrary real-world problems in a given amount of time. More generally, the empirical success of EAs is not easily explained in terms of the EA theory available today.

The population approach of EAs usually leads to high computational demands. Since EAs are easily parallelized, this is becoming less of a problem as available hardware power increases and parallel computers are more and more common. Furthermore, the optimization process can be rather inefficient in
the final search phase, particularly for GAs. Hybridizing with a quick local optimizer can cater for this problem, though.

With a few exceptions (such as grouping problems), it seems very difficult today to predict in advance whether for a particular real-world optimization problem EAs will produce results superior to those of similar modern heuristics such as threshold accepting or SA. The most important point is really to account for the properties of the problem in designing the algorithm, and here EAs offer a large toolbox to choose from.

F1.2.4 Conclusions

Over the last couple of years, interest in EAs has risen considerably amongst researchers and practitioners in the management domain, although we have not seen the major breakthrough of EAs in practical applications, yet. Most people have been attracted by GAs, while ESs, EP, and GP are not so widely known. GP is the newest technique and is just reaching the level of practical applicability, particularly in the financial sector. Even though GAs are most common, this should not be interpreted as superiority over other EA types. It rather seems to be a good ‘infrastructure’ that contributes to the trend for GAs.

The majority of applications analyzed here concern GAs in combinatorial optimization. Many researchers focus on standard problems to test the quality of their algorithms. The results are mixed. This is partly due to the enormous difficulties associated with conducting meaningful empirical comparisons between optimization techniques. Moreover, the NFL theorem tells us that one should not expect to find a universally superior optimization method. However, the current efforts to develop professional EA tools and parallelize EA applications, and the exponentially growing number of EA researchers, will lead to more practical applications in the future and a better understanding of the relative advantages and weaknesses of the evolutionary approach. Figure F1.2.3 is an attempt to assess the current position of EAs as an optimization method with respect to the technological life cycle.

![Figure F1.2.3. An estimation of the current state of EAs as an optimization method in a life cycle model as of July 1996.](image)

There is evidence for the robustness of EAs in stochastic optimization where the evaluation involves noise or requires an approximation of the true objective function value (Grefenstette and Fitzpatrick 1985, Hammel and Bäck 1994, Nissen and Biethahn 1995). Encouraging first results have also been achieved in time-varying environments employing nonstandard concepts such as diploidy (Smith 1987, Smith and Goldberg 1992, Dasgupta and McGregor 1992, Ng and Wong 1995). EAs also have been shown to work well on integer programming problems which are presently difficult to solve with conventional techniques such as linear programming for large or nonlinear instances (Bean and Hadj-Alouane 1992, Hadj-Alouane and Bean 1992, Khuri et al 1994, Khuri and Bäck 1994, Rudolph 1994).

Currently, EAs are becoming more and more integrated as an optimization module in large software products (e.g. for production planning). Thereby, the end user is often unaware that an evolutionary approach to problem solving is employed. Integrating and hybridizing EAs with other techniques is a most promising research direction. It aims at combining the relative advantages of different problem solving methods and leads to powerful tools for practical applications.
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Appendix A. Tables

Tables F1.2.1, F1.2.2, and F1.2.3 list, respectively, the use of EAs in practical management applications, in application-oriented research in management science, and in other classical optimization problems. The references cited in these tables are listed in Appendix B. In tables F1.2.1 and F1.2.2, the ‘Earliest known’ column indicates the year of the earliest known presentation.

<table>
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<th>References</th>
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<td>1. Industry</td>
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<td>1.1 Production</td>
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<td>[FULK93b]</td>
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<td>Simultaneous planning of production program, lotsizes, and production sequence in the wallpaper industry</td>
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<td>Balancing combustion between multiple burners in furnaces and boiler plants</td>
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<td>[NOCH90]</td>
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### Table F1.2.1. Practical applications of EAs in management (continued).

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<td>Allocating investments to health service programs</td>
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<td>Scheduling an F-14 flight simulator to pilots</td>
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### Table F1.2.2. EAs in application-oriented research in management science. The third column, headed ‘No’, indicates the number of projects.

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### Table F1.2.2.

EAs in application-oriented research in management science. The third column, headed ‘No’, indicates the number of projects (continued).

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Management applications and other classical optimization problems

Table F1.2.2. EAs in application-oriented research in management science. The third column, headed ‘No’, indicates the number of projects (continued).

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| Personnel management        | Employee staffing and scheduling                        | 3  | [EAST93], [LEVI93a,b,95,96], [TANO95] | 1993–1995     |
|                             | Talent scheduling                                        | 1  | [NORD94]    | 1994          |
|                             | Audit staff scheduling                                   | 1  | [SALE94]    | 1994          |

| Telecommunication           | Terminal assignment in a telecommunications network      | 1  | [ABUA94a,b] | 1994          |
|                             | Minimum-broadcast-time problem                           | 1  | [HOEL96a]   | 1996          |
|                             | Finding investigator tours in telecommunication networks | 1  | [HOEL96b]   | 1996          |
|                             | Analysis of call and service processing in telecommunications | 1  | [SINK95] | 1995          |
|                             | Routing in communication networks                        | 1  | [CARS95]    | 1995          |
|                             | Design of communication networks                         | 1  | [CLIT89]    | 1989          |

| Miscellaneous               | General resource allocation problems                     | 2  | [SCHO76], [BEAN92a] | 1976          |
|                             | Forecasting time series data in economic systems         | 1  | [LEE95a]     | 1995          |
|                             | Investigation of taxation-induced interactions in capital budgeting | 1  | [BERR93] | 1993          |

### Table F1.2.3. EAs in other classical optimization problems.

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<td>[BÄCK96c]</td>
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<td>Quadratic assignment problem</td>
<td>[COHO86], [BROW89], [MUHL89, 90, 91a], [LI90], [HUNT91], [MAN91, 95],</td>
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<td>[BEAN92a], [COLO92b], [LI92], [NISS92, 93a, 94a, c, d, e], [POON92],</td>
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<td>Assignment problems</td>
<td>[CART93a], [LEVI93c]</td>
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<td>Knapsack problems</td>
<td>[HENS86], [GOLD87], [SMIT87, 92a], [DASG92], [GORD93], [THIE93],</td>
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<td>[KHUR94a], [MICH94], [NG95], [BÄCK96b]</td>
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<td>[LASZ90, 91], [COHO91a, b], [COLL91], [HUL91, 92], [JONE91], [DRI92],</td>
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<td>[HÖHN95], [KAHN95], [MENO95], [BÄCK96b]</td>
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<td>[SANN88], [HOU90, 92], [LAWT92], [SMIT92c], [KIDW93], [ADIT94a, b],</td>
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<td>[PIC94], [SCHW94], [SEIB94], [WAH95]</td>
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<td>Graph coloring</td>
<td>[DAVI90, 91], [EIBE94a], [COST95], [FLEU95], [KHUR94b, c]</td>
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<td>Minimum vertex cover</td>
<td>[KHUR94b, c]</td>
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<td>Miscellaneous graph problems</td>
<td>[BÄCK94, 96b], [PALM94a], [ABUA95a, b, 96], [PIGG95]</td>
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<td>[LIEN94a, b], [MARI94]</td>
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<td>Task allocation</td>
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<td>Load balancing in a database</td>
<td>[ALBA95]</td>
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