Guest Editorial

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Evolutionary Complex Engineering Optimization: Opportunities and Challenges

Evolutionary algorithms (EAs) including other meta-heuristics such as particle swarm optimization and differential evolution have shown to be powerful for global optimization of a wide range of problems. In recent years, huge research effort has been devoted to solving complex engineering optimization (CEO) problems. Among others, CEO problems are often subject to large amount of uncertainties, such as varying environmental conditions, system degeneration, or changing customer demand; they are highly constrained, where the constraints themselves can also change over time; computationally expensive and need to satisfy multiple criteria involving multiple disciplines; they usually consist of mutually dependent subsystems having a high number of possibly correlated decision variables. Furthermore, complex engineering optimization in most cases is embedded into a larger design process involving several teams and tools working sequentially and in parallel on a variety of temporally and spatially decomposed sub-systems. As a result, a number of new research areas have emerged, including evolutionary optimization in dynamic and uncertain environments [1], [2], surrogate-assisted evolutionary optimization [3], multi- and many-objective optimization [4], [5], large-scale optimization [6], and integrated control and optimization [7], [8], just to name a few.

Despite the fact that the above topics are motivated from real-world challenges, not much of the research results in the above areas have been applied to solving real-world problems and most challenges in complex engineering optimization remain unsolved. Thus, concerns have been raised about the relevance of these lines of research to real-world problems. First, it remains unclear whether the challenges addressed in these areas are of practical significance in the real world. For example, in evolutionary dynamic optimization, most algorithms have been designed to closely track the changing optimum. This is ideal in principle if the designed algorithm is able to follow the moving optimum at any time instant. However, frequent changes of the optimal design will not only be constrained by time for implementing the new designs, but will also incur very high cost, which makes it impractical in the real-world. One recent idea to address this issue is to find optimal solutions that are robust over time so that optimal solutions that change most slowly will be identified to minimize the need to change the design [9], which can be seen as a trade-off between optimum tracking and robustness.

Second, a large number of test problems have been designed for benchmarking the performance of different meta-heuristics. Such test problems are meant to reflect the hardness of real-world problems and have widely been used in dynamic optimization, multi-objective optimization, constrained optimization as well as in large-scale optimization. For publishing a paper, these test problems have become almost a standard for demonstrating the advantage of newly proposed algorithms over the state-of-the-art. However, little thought has been given to whether these popular suits of test problems are of significance in the real-world, i.e. how much the test problems are relevant to real optimization cases.

Third, it is no longer straightforward to come up with one single well-defined performance indicator to compare the performance of the developed algorithms. This is true for multi-objective optimization, where the quality of the achieved solution set must be assessed using more than one performance indicator, including accuracy and diversity. In addition, the quality of solutions can also be subjective, often depending on the preference of a human decision maker. The situation becomes worse in many-objective optimization, where the number of objectives considered is often very high. Obviously, comparing an extremely small set of solutions in a huge space makes little sense and can even become misleading without a clear preference. Even the seemingly straightforward visualization of the results of a many objective optimization process can be very awkward due to the high dimensionality of the objective space.

To address the above-mentioned concerns, the first question one might raise is: What makes a CEO problem really difficult to solve? It is not straightforward to provide a simple answer to this question, as it is inherently problem dependent. In the following, we attempt to discuss a few points, which—we hope—can shed some light on the question.

If one has had experience in solving real-world CEO problems, one will be

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aware that much effort needs to be expended in solving a number of issues even before the actual optimization can be conducted. The first issue is the problem formulation, including definition of the objectives, constraints and the representation, which defines the decision variables. Difficulties may arise from that fact that many CEO problems consist of a number of sub-systems or sub-processes that are inter-dependent, and optimization of the individual sub-systems separately may not lead to a globally optimal solution. At the same time, the representation of the complete problem at once is often prohibited by the very high dimensionality. Problems from aerodynamic shape optimization are good examples, where a holistic representation of e.g. a racing car would easily consist of thousands of decision variables. Therefore, representations have to be defined which are inherently incomplete covering only part of the design space. Methods to cope with this deficiency are required, e.g. by choosing an optimal spatio-temporal decomposition of the problem or by adaptively changing the representation during the search process focusing on those design areas which are highly sensitive.

In addition, CEO problems may not be easily described by explicit mathematical models and are subject to a large amount of uncertainty. Understanding and properly formulating an optimization problem is itself part of the overall problem-solving process and it typically requires several iterations between the optimization expert and the application engineer often also involving a simulation specialist working on the particular problem. Many simulation methods are iterative approaches (e.g. CFD or FEM) with a residual error and a problem-dependent setup (mesh type and size) that strongly interacts with the optimization methodology. Another typical class of CEO problems are plant-wide product process optimization [7], e.g., optimization of the global operation of mineral processing, which is composed of multiple coupled processes such as ore crushing, grinding and regrinding, and selection. No exact mathematical models are available to describe such processes and several objectives including product quality, energy efficiency and productivity need to be satisfied. One particularly interesting issue in such process optimization problems is that both optimization and control are involved. An integrated control and optimization strategy may not only lead to global optimization, but may also offer a new approach to deal with uncertainties that optimally balance dynamic optimization and robustness.

Another example is aircraft design, where various parts of an aircraft, e.g., fuselage, wing and tail must be designed in an integrated and holistic way to ensure that each part is designed for the optimization of the whole aircraft with respect to multiple objectives including energy efficiency, emission reduction and safe operations. To deal with the optimization of such CEO problems, a systems engineering perspective, i.e. a holistic problem view must be taken as suggested in [7], [10].

Similar challenges can be identified for the optimization of passenger cars, where not just the optimization criteria from several engineering disciplines such as structural safety (crash), aerodynamics and thermodynamics have to be integrated, but also issues of aesthetic design, cost efficient manufacturing, and product disposal (recycling) have to be taken into account. The optimization framework basically embraces and interrelates all segments in the product life cycle management process that is the backbone of most complex engineering problems. In a sense, the optimization framework itself is hierarchically organized consisting of many sub optimization problems that are allowed to operate on different time scales from minutes to months and that need to interact with each other and with the respective decision makers during the complete development, procurement, manufacturing and service processes. In real-world challenges tuning the algorithm to be *embeddable* into such a complex framework is often more relevant than providing optimization results that are marginally better on a limited test suite than state of the art methods. This shall not belittle the effort teams have been taken and are taking to improve numerical and combinatorial optimization methods, but shall emphasize that often the needs in a practical CEO challenge are different. At the same time, evolutionary algorithms (EAs) including other meta-heuristics are very promising candidates and approaches for fitting into complex design frameworks, because of their inherent robustness, flexibility and adaptability.

Optimization algorithms developed for solving CEO problems must be scalable to the number of decision variables as well as to the number of objectives and be able to deal with uncertainties, by tracking the optimum or finding robust optimal solutions or by identifying optimal (acceptable) solutions that are robust over time when frequent change of solution is prohibitive. Whilst algorithms proposed for solving large-scale and many-objective optimization tasks are very helpful, it is equally desirable if the optimization algorithm is able to identify a small number (two to three) of the most critical objectives. To this end, preference-based interactive search may be more tractable than an uninformed search aiming to find all Pareto-optimal solutions, if the number of objectives cannot be reduced. This is one example where engineering data mining, knowledge acquisition, see e.g. [13], and visualization techniques become more and more important to guide the interactive search process, to formulate the initial problem or to identify the most appropriate problem representation, which is directly related to reducing the number of decision variables.

Here, we naturally come to another important question that may arise in dealing with CEO problems, i.e., how to make sure that a developed optimization algorithm is able to gain problem-specific knowledge during optimization so that the search is more efficient, adaptable and well prepared for change. To this end, hyper-heuristics [11] that systematically integrate optimization and learning techniques can be promising approaches. Incorporation of learning techniques to

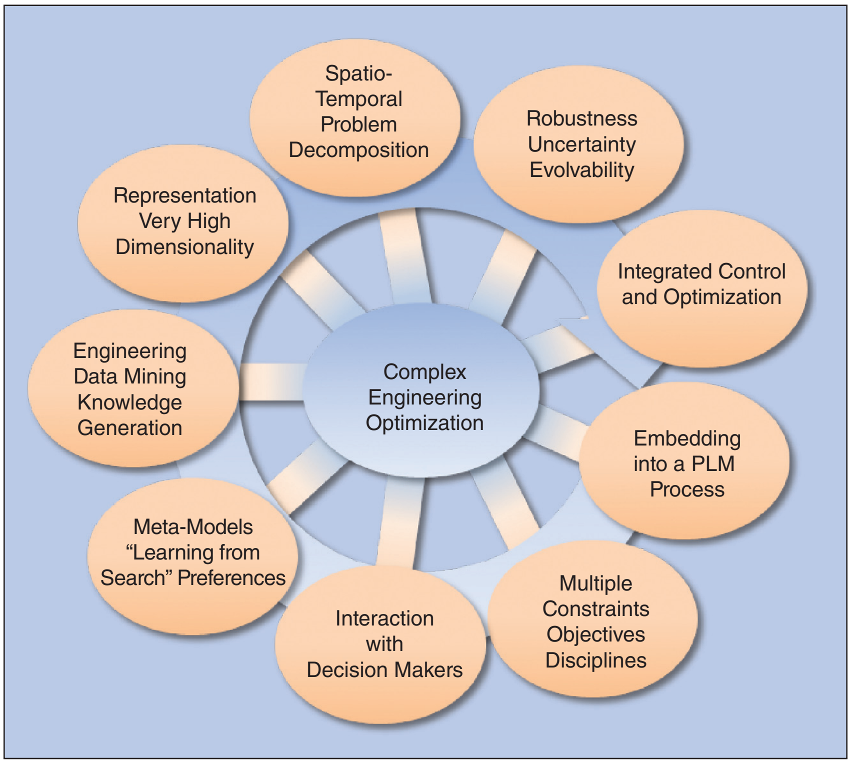

FIGURE 1 Main challenges and requirements of CEO.

gain problem specific knowledge can be beneficial not only for capturing the problem structure to select the right search strategy, learning user preference in multi- and many-objective optimization, but also in identifying the most relevant search space and modeling of the unknown or partially known system for optimization and control [12]. Another strategy used in biology to cope with uncertain environments is to be prepared for changes. To this end, an optimization algorithm should be evolvable, i.e., be able to find optimal solutions that can easily adapt to a new environment. Methods for finding robust (robust over time) optimal solutions in changing environments [8] can be seen as a specific example.

Figure 1 summarizes the main challenges and requirements in dealing with CEO problems.

This special issue aims to promote the application of EAs and other meta-heuristics to solving real-world complex engineering optimization problems. In response to the Call for Papers, nine papers have been submitted. After a standard peer-review process, four papers have been selected to include in the special issue. These four papers represent recent advances in evolutionary optimization of a wide range of real-world problems, including optimization of multi-UAV (unmanned aerial vehicles) systems for adaptive 3D formation configuration, multi-objective optimization of wall-following mobile robots, self-organization of internet of things, and discovering low-energy transition states of small, non-cyclic molecules. These results illustrate, to various degrees, the challenges that need to be addressed in solving complex optimization problems.

In the paper "Hybrid particle swarm optimization and genetic algorithm for multi-UAV formation reconfiguration in 3-D space" by *Duan et al*, a hybrid optimization strategy combining a genetic algorithm (GA) and particle swarm optimization (PSO) has been proposed in order to find an optimal control strategy for multi-UAV formation reconfiguration problem in 3-D space. The problem is formulated as an optimization problem involving the minimization for a specified payoff function with state relative constraints. The proposed algorithm that takes advantage of the global search ability of GA and the fast convergence property of PSO has been shown to be able to solve the time-optimal control for single- and multi-formation reconfiguration problems.

In the article "Multi-objective rule-coded advanced continuous-ant-colony-optimized fuzzy controller for robot wall-following control" by *Hsu and Juang*, both structure and parameters of a fuzzy controller are optimized using ant colony optimization (ACO). In this optimization task, both discrete and continuous decision parameters need to be optimized, requiring that the search algorithm is able to handle the search of both types of decision variables. Meanwhile, multiple objectives, including maximization of wall-following accuracy, minimization of the time for completing the wall-following task, maximization of the smoothness in changing the steering angles and the minimization of the number of fuzzy rules have been taken into account. No fuzzy rules need to be predefined and all data for generating the rules are collected online.

The Internet of Things (IoT) is a representative new development in communication and networking technologies in the past decades, which is characterized by its large-scale heterogeneous network elements and large amount of uncertainty in the sensed information in a dynamic, external environment it usually resides in. In the article "An intelligent self-organization scheme inspired from the endocrine regulation principle for the complex Internet of Things" by *Ding et al*, it is shown that an artificial endocrine system inspired by the human hormone system can provide solutions to the often seen challenges in solving real-world problems such as scalability, heterogeneity and complexity. By introducing the hormone mechanism with different purposes as the media for the information transmission and data sharing among the nodes in the IoT, the nodes can collaborate with each other and work in a cooperative way.

Memetic algorithms are one type of the "hyper-heuristics" that can acquire problem-specific knowledge during optimization to enhance search efficiency. In the paper titled "Discovering unique, low-energy transition states of small, non-cyclic molecules using evolutionary molecular memetic computing" by *Ellabaan et al*, a novel evolutionary Molecular Memetic Computing (MMC) methodology is presented that requires little domain knowledge. The essence of MMC lies in the tree-based representation of non-cyclic molecules and the covalent-bond-driven evolutionary operators in addition to the typical backbone of memetic algorithms—the population-based global search method and the individual-based life-time learning procedure. This work confirms that an efficient representation of the optimization problem and automatic acquisition and reuse of problem knowledge can be critical for solving complex optimization problems.

The four papers in this special issue may just illustrate a subset of the challenges in solving real-world CEO problems. Nevertheless, we believe that all of the papers are interesting, informative and will help us to better understand the promises and challenges in evolutionary optimization of complex engineering problems. We are confident that in the near future, more sophisticated work on evolutionary optimization of CEO problems will be reported. We would like to thank Dr. Kay Chen Tan, the Editor-in-Chief, for giving us the opportunity to guest-edit this special issue. Thanks also go to all authors who submitted their work to this special issue and reviewers for providing us constructive and insightful reviews within a very tight schedule.

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