Mathematical and Computational Applications

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Editorial

Numerical and Evolutionary Optimization 2020

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Solving scientific and engineering problems from the real world is a very complicated task, currently; hence, the development of powerful search and optimization techniques is of great importance. Two well-established fields focus on this task: (i) traditional numerical optimization techniques and (ii) bio-inspired metaheuristic methods. Both general approaches have unique strengths and weaknesses, allowing researchers to solve some challenging problems but causing them to fail in others. The goal of the Numerical and Evolutionary Optimization (NEO) workshop series is to gather people from both fields to discuss, compare, and merge these complementary perspectives. Collaborative work allows researchers to maximize the strengths and to minimize the weaknesses of both paradigms. NEO also intends to help researchers in these fields to understand and tackle real-world problems such as pattern recognition, routing, energy, lines of production, prediction, and modeling, among others.

This Special Issue was inspired by the 8th International Workshop on Numerical and Evolutionary Optimization (NEO 2020), held as online event and hosted by the Universidad de la Sierra Juárez, Oaxaca, Mexico, the Universidad Veracruzana, Xalapa, Mexico, and the Cinvestav-IPN, Mexico City, Mexico.

The Special Issue consists of 16 research papers, as follows. In [1], Deb et al. survey surrogate modeling approaches for the numerical treatment of multi-objective optimization problems. Moreover, the authors propose an adaptive switching-based metamodeling approach, yielding results that are highly competitive to the state-of-the-art.

The following 10 papers are devoted to the design of new algorithms for particular optimization problems. In [2], Berkemeier and Peitz present a local trust region descent algorithm for unconstrained and convexly constrained multi-objective optimization problems. The method targets at problems that have at least one objective function that is computationally expensive. Convergence of the derivative-free method to a Pareto critical point is proven.

In [3], Perez-Villafuerte et al. propose a new hybrid multi-objective optimization evolutionary algorithm, called P-HMCSGA, that allows the incorporation of decision makers' preferences in the early stages of the optimization process. The strength of the novel method is illustrated in real-size multi-objective project portfolio problems.

In [4], Castellanos-Alvarez et al. propose a method, NSGA-III-P, for the integration of preferences into a multi-objective evolutionary algorithm using ordinal multi-criteria classification. Numerical results show that the new method is capable of identifying the proper region of interest as specified by the decision maker.

In [5], Macias-Escobar et al. propose a new interactive recommendation system for the decision-making process based on the characterization of cognitive tasks. The system focuses on a user–system interaction that guides the search towards the best solution considering a decision maker's preferences. The developed prototype has been assessed by several test users, leading to a satisfying score and high overall acceptance.

In [6], Guzmán-Gaspar et al. present an empirical comparison of the standard differential evolution (DE) against three random sampling methods to solve particular robust

optimization problems in dynamic environments. The findings indicate that DE is a suitable algorithm to deal with this type of dynamic search space when a survival time approach is considered.

In [7], Sánchez-Hernández et al. address the protein folding problem. To this end, they present the algorithm GRSA-SSP, a hybrid of golden ratio-simulated annealing with a secondary structure prediction. Numerical results show that the new algorithm competes with the state-of-the-art methods in small peptides, but not when predicting the largest peptides.

In [8], Estrada-Padilla et al. propose a new methodology to deal with uncertainties in multi-objective portfolio optimization problems by using fuzzy numbers. The results show a significant difference in performance favoring the proposed steady-state algorithm based on the fuzzy adaptive multi-objective evolutionary (FAME) methodology.

In [9], Frausto-Solis et al. propose two multi-objective job shop scheduling metaheuristics based on simulated annealing: Chaotic Multi-Objective Simulated Annealing (CMOSA) and Chaotic Multi-Objective Threshold Accepting (CMOTA). Numerical results indicate that the two novel methods are highly competitive with the state-of-the-art methods.

In [10], de la Fraga analyzes the use of numbers with 16 bits in a conventional Differential Evolution (DE) algorithm. It is shown that the additional use of fixed point arithmetic can speed up the evaluation time of the objective function.

In [11], Beltrán et al. deal with a continuation method for the mumerical treatment of multi-objective optimization problems. More precisely, the Pareto Tracer is extended for the efficient numerical treatment of general inequalities, which greatly enhances its applicability.

The last five papers of this Special Issue deal with the numerical treatment of particular applications that arise in the real world. In [12], López et al. present some preliminary results of a study of 17 interconnected power generation plants situated in eastern Mexico. The study shows that fossil fuel plants, besides emitting greenhouse gases that affect human health and the environment, incur maintenance expenses even without operation.

In [13], Frausto-Solis et al. propose a new method designed to confirm cases of COVID-19 in the United States, Mexico, Brazil, and Colombia, based on Component Transformation and Convolutional Neural Networks. Numerical results show that it consistently achieves highly competitive results in terms of the MAPE metric.

In [14], Cai et al. propose and analyze a novel framework for multi-objective risk-informed desicion support systems for the drainage rehabilitation problem. This study shows that the conventional framework can be significantly improved in terms of calculation speed and cost-effectiveness by removing the constraint function and adding more objective functions.

In [15], Bahreini Toussi et al. investigate the impact forces caused by liquid storage tanks which can lead to structural damage as well as economic and environmental losses. To this end, an OpenFOAM numerical model is used to simulate various tank sizes with different liquid heights.

Finally, in [16], Castañeda-Aviña et al. design an analog circuit, a voltage-controlled oscillator (VCO), optimized using Differential Evolution. It is shown that the suggested approach yields highly robust solutions.

Conflicts of Interest: The authors declare no conflict of interest.

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